An educational neuroscience perspective on tutoring: To what extent can electrophysiological measures improve the contingency of tutor scaffolding and feedback?

Julien Mercier, Mélanie Bédard
mercier.julien@uqam.ca, bedard.melanie.2@uqam.ca

University of Quebec in Montreal

Abstract. The efficacy of tutoring as an instructional strategy mainly lies on the moment-by-moment correspondence between the help provided by a tutor and the tutee's learning needs. The model presented in this paper emphasizes the pivotal role of monitoring and regulation, both by the tutor and the tutee, in attaining and maintaining affective and cognitive states conducive to student's learning. This perspective highlights the hypothesis that the scarcity of the information that the tutor and tutee have access to during natural interaction leads to suboptimal learning interactions. As a potential response to this lack of information, it is argued that methodologies from cognitive and affective neuroscience can provide pertinent information during or after a learning interaction, and that this information can significantly empower students and tutors. Projected empirical research could lead to a dramatic reinterpretation of 35 years of already fruitful tutoring research.

Keywords: educational neuroscience, tutoring, monitoring, regulation, contingency

Introduction

It is suggested in this paper that an educational neuroscience perspective on human tutoring research may further improve the long-recognized efficacy of this learning context, in which an expert tutor interacts with a student as she works on a problem that she cannot solve without help. Scaffolding and feedback are the most efficient instructional tactics used by the tutor in one-on-one tutoring, irrespective of the learning domain such as science education or reading, but they have to be contingent on the student's needs (VanLehn, 2011; Wood & Wood, 1999). In this context, contingency is the moment-by-moment correspondence between the help provided and the student's learning needs. Accordingly, scaffolding and feedback are means to incrementally reduce the discrepancy between current and desired understanding during the course of a learning situation. Scaffolding is defined as the provision of guidance to elicit particular actions on the part of the student (VanLehn, 2011; Wood & Wood, 1999). This scaffolding may be dynamic or fixed: fixed scaffolding refers to non-interactive help such as printed written materials whereas dynamic scaffolding concerns information modulated by the situation (Kim & Hannafin, 2011) such as help provided at the request of the tutee or at the initiative of the tutor (Chi et al., 2001). In contrast with some conceptualizations of feedback which blur the distinction between feedback and scaffolding (see Hattie & Timperley, 2007), scaffolding is different from feedback in that it is not a response to previous behavior, but is instead a prompt for a desirable behavior. Feedback mainly concerns information about aspects of the student's performance or understanding (VanLehn, 2011). Efficient scaffolding and feedback is related to critical dimensions of the current learning goal (Hattie & Timperley, 2007).

The goal of this article is to examine an important issue in current tutoring research, namely interaction granularity and its impact on learning, and to suggest that an educational neuroscience perspective may contribute to characterize and improve tutoring interactions. To do so, a conceptualization of a tutoring interaction as joint monitoring and regulation is presented, along with a proof of concept of a process-oriented integration of electrophysiological data in tutoring research.

An important issue in current tutoring research: interaction granularity and contingency of scaffolding and feedback

Chi and her colleagues (2001), have shown that the effectiveness of tutoring rests on and demonstrates the power of human agency (either by the tutor and the tutee), a notion that according to Ferrari (2011), researchers in educational neuroscience must include in their prescriptions for teaching. This also acts as a countermeasure to the deterministic aura of cognitive neuroscience in the mind of many educators, who may falsely believe that the functioning of the brain represents the main constraints for learning (Dekker et al., 2012).

In a tutoring situation, the tutor has to determine online the state of the learner according to a number of dimensions important for learning, such as cognitive and affective states (VanLehn, 2011). The tutor has to do so on the basis of the information available regarding the tutee: the conversation (in a broad sense, and including gesture, facial expressions, etc.) and the problem-solving trace (what the learner has done up to the current point to solve the problem). Then the tutor provides feedback concerning the past performance of the student, or orients the next steps by means of scaffolding tactics. The tutee also monitors his own performance using metacognitive information in addition to the problem-solving trace (Efklides, 2011).

Although research has shown that tutoring is a natural, almost routine human activity (Wood, Bruner & Ross, 1976; Graesser et al., 1997), no studies have yet tackled the daunting question of establishing benchmarks of optimization of contingency of a tutoring interaction, and measuring gaps between optimal and sub-optimal contingency on a moment-to-moment basis (see VanLehn, 2011). Observing and characterizing those gaps may put an emphasis on the challenge involved in monitoring and regulating the student's learning in such complex circumstances, but also may provide cues that can be used to improve both the tutor's and the learner's decision-making during tutoring.

VanLehn's (2011) comparison of human tutoring with various ITS provides a good starting point for our case that educational neuroscience may contribute important insights in tutoring research by reviewing major hypotheses regarding the greater efficacy of human tutoring over other teaching methods. Many explanations for the efficacy of human tutoring are ruled out on the basis of empirical studies. (1) human tutors do not hold and use detailed diagnostic assessments of the students state (because tutors don't have that information (such as misconceptions, false beliefs, and buggy skills) from the trace or dialogue); (2) human tutors do not provide individualized task selection (ITSs do more of this); (3) human tutors do not use sophisticated tutorial strategies; (4) learner's control of dialogues (permitted by greater responsiveness on the part of a human tutor) is not supported either; (5) human tutors possess broader domain knowledge but this knowledge is not intervening significantly during the tutorial interaction; and finally, (6) human tutors do not have a better positive impact on student motivation. Two hypotheses are supported by research: the effectiveness of human tutors rests on (1) the feedback and (2) the scaffolding they provide. There is a lot of confusion in the current literature about the use of the terms feedback and scaffolding. A pivotal distinction of which we are reminded by VanLehn (2011) is that feedback occurs after a student's target move, whereas scaffolding is proactive and occurs before a student's target move. In other words, feedback is used to validate or to invalidate and correct a move that has previously occurred, whereas scaffolding is used to elicit a desired move immediately after this scaffolding is provided.

In addition to the feedback and the scaffolding hypotheses, the interaction plateau hypothesis provides another complementary and empirically-validated explanation for the efficacy of human tutoring (VanLehn, 2011). The principle of the interaction plateau hypothesis is that as interaction granularity decreases, the efficacy of tutoring on learning outcomes increases only to a given granularity. This granularity corresponds to step-based tutoring, in which feedback is given in association with each step in a problem-solving solution. Current research is capitalizing on the demonstrated success of step-based tutors: Aleven et al. (2009) extended the development of step-based tutors from linear problems to more complex problems that can be solved through multiple solution paths.

The interaction granularity can be explored in terms of timescales, in which more complex, slower operations are constituted of sub-processes occurring faster (Newell, 1990). From a temporal perspective, step-based tutoring corresponds to tens of seconds, or the unit-task level (see Anderson, 2002). Those steps correspond to the steps normally done for solving a given problem. By contrast, sub-steps concern operations required to perform the steps that normally remain implicit in problem solving. The interaction plateau hypothesis shows that this level of detail in tutoring does not provide better learning gains than step-based tutoring. This is also true of human tutoring, in which the temporal granularity is potentially even finer. Anderson (2002) argued for the importance of sub-steps (from tens of seconds (substeps) down to tenths of seconds (Newell's (1990) deliberate acts)) to diagnose student's mastery and predict retention and transfer.

It can be helpful to discuss the interaction plateau hypothesis presented before in light of a powerful principle of tutoring: contingency (Wood, Bruner & Ross, 1976). Contingency is a property of scaffolding (Wood & Wood, 1999; van de Pol, Volman & Beishuizen, 2011). Contingency is achieved when the tutor provides help when needed and draws back to leave more responsibility to the learner, a process called fading, according to the "shift rule" (Wood, Bruner & Ross, 1976). This rule involves providing more support on the next intervention if the tutee fails and providing less support in case of success. An experimental study in which contingency was manipulated shows that a careful application of the "shift rule" leads to better learning outcomes (Pratt & Savoy-Levine, 1998). The results show that providing only the appropriate help is better than providing more help than needed. The tutor must infer the current goals of the tutee to have a reasonable probability of offering contingent support (Gobet & Wood, 1999).

Original formulations of the notion of contingency imply that only the tutor, human or computer, is contributing proactively in the interaction, a process illustrated by Frederiksen, Roy & Bédard (1995). The notion has since been broadened to take into account the findings regarding the contribution of the student to the interaction, as investigated by Chi et al. (2001). Although it is the tutor that provides help, the student has his share of responsibility in the interaction, having to seek help strategically (Mercier & Frederiksen, 2007; 2008; Aleven et al., 2003). There is also troubling evidence that the accuracy of learners' judgements about their need for help reflects prior knowledge (Wood & Wood, 1999). However, long help-seeking latencies are correlated with positive learning outcomes, and can be explained by the fact that this can reflect self-explanations on the part of the learner (Wood & Wood, 1999). Therefore, contingency of tutoring can be seen as an emergent property of the interaction between the tutor and the student. Yet, the advent of Interactive Learning Environments (ILEs), computer-based learning tools providing on-demand help, has led to reconsider contingency in this context as entirely dependent on the student's decisions. Indeed, the tutor initiative that is required for contingency as originally formulated is absent from non-modeling ILEs.

By postulating the interaction plateau hypothesis, VanLehn's (2011) analysis discredited the interaction granularity hypothesis (according to which learning gains are correlated with maximally fine-grained feedback and scaffolding), and this interpretation of current research hinges on empirical work showing diminishing returns of finer-grained feedback and scaffolding. It must be kept in mind however that neither human tutors nor ITSs are perfect, and that the feedback and scaffolding they provide may be flawed sometimes, as VanLehn points out. This is especially important when learning is conceptualized as cumulative changes in small units of knowledge (Anderson, 2002). Thus, an alternative interpretation for the currently discredited interaction granularity hypothesis, given the current state of the research can be proposed: the key for accurate feedback and scaffolding at a given grain size is adequate information about the learner at that grain size. It can be argued that available research has not demonstrated that this information was available and used to improve the contingency of tutoring.

In addition, the studies reviewed may be thought to indicate that theoretical and technical developments are required to obtain such information during the course of a tutoring interaction. VanLehn asserted that "Human tutoring is finer grained than substep-based tutoring because its granularity is unconstrained" (2011, p.204). Alternatively, it can be postulated that the granularity of human tutoring, rather than being unconstrained, is limited at the finer time scale to the granularity of conversation and speech (seconds). Moreover, the granularity of conversation and speech (seconds) is two orders of magnitude above the granularity of the lowest-level processes associated with learning (10 milliseconds), as shown by Anderson (2002). Moreover, the interaction plateau hypothesis put in relation with the feedback and scaffolding hypotheses, shows exactly the grain size interval (seconds to 10 miliseconds) above which adequate feedback and scaffolding are required to further optimize learning from tutoring, and get to the 2 standard deviations effect size that remains the goal of the tutoring research community (VanLehn, 2011). The question is how to relate events occurring at those different grain sizes, and is discussed in an upcoming section. VanLenh's demonstration shows that the alternative explanation put forward here is a testable claim given adequate concepts and methodology.

The correlation of transitions in conversation with tutee's global learning gains is very informative. However, a consideration of learning gains associated with elements of a hierarchical decomposition of the learning domain would be even more sensible (even when those are aggregated over some given characteristic), in the sense, as Boyer et al. (2011) point out, that all transitions should be related to learning gains, either positively or negatively. When tutoring research reaches this point, major prescriptions for tutoring will be formulated.

In sum, the issue identified previously can be related to the principle of contingency. Contingency implies that the trace of events regarding the student is the most important driving factor in tutoring, both human and ILEs. In this light, the provision of feedback and scaffolding in tutoring can be understood as a self-, other-, or co-regulatory activity targeted at student's learning (see Panadero & Järvelä, 2015). Globally, current research on tutoring has not completely examined the regulatory aspect of tutoring, and the importance of monitoring in this process should be a focal point of future research, as well as the decision-making process that leads to regulation on the basis of monitoring. Finally, the possibility of tutoring research of formulating pedagogical prescriptions rests heavily on a clear conceptualization and measure of learning. What is needed within a focus on learning trajectories is the fine-grained "signature" of learning in authentic contexts. Behavioral data may not be sufficient, and it is suggested in the next section that psychophysiological data from cognitive and affective neuroscience theory and methodology may lead to significant advances in this endeavor.

Re-examining the tutorial interaction as a joint monitoring and regulation process

Considering recent research, the proposed view appears to be of limited use for the study of either how tutors help students or how students learn from tutoring. Relatively more detailed models of monitoring and regulation processes were elaborated for a variety of contexts, including for example how an intelligent tutoring system helps scaffolding self-regulated learning (Graesser & McNamara, 2010), or how students seek help from tutors or computer tools (Karabenick, 2011; Roll et al., 2011; Mercier & Frederiksen, 2008; 2007). Moreover, current event-based conceptualizations of self-regulated learning integrate personal traits with task demands (Efklides, 2011). However, the suggested model is critical in examining the moment-by-moment, complex and dynamic interplay between the agency of the tutor and the one of the student, which has been shown to be the main determinant of student's learning (Chi et al., 2001). It focuses on the notion that tutoring is a joint and asymmetrical performance involving a tutor and a tutee with fluctuating levels of success which varies greatly from person to person, from session to session, and even from moment to moment. It also stresses the importance of a fine-grained trace of pertinent affective and cognitive processes for an optimal tutoring interaction, and raises questions regarding the necessary information, how to obtain this information, and which tutor and student "regulation policies" are most appropriate for student's learning.

A joint decision-making model

Before discussing how psychophysiological measures could significantly contribute to tutoring research, it appears relevant to highlight a model that describes aspects of how a tutor and a tutee function in a tutoring interaction. The proposed model discusses the assumption that decisions made by the learner and tutor are or should be aimed at attaining and maintaining desirable states in the learner, and in the properties of the interaction, reputedly conducive to learning. Afterwards, critical information for the optimization of a tutoring interaction through monitoring and regulation is presented. The ability to reach and maintain affective and cognitive states optimally conducive to learning is a critical aspect of students' success. This can be the result of the scaffolding provided through the interaction with a teacher or a computer tool (referred to as co- or other-regulation by Volet, Vauras & Salonen (2009) and Järvelä & Hadwin (2013)). The necessary skills can also be developed in a learner as self-regulation. A program of research based on this model concerns (1) the identification of critical aspects of learning processes (both affective and cognitive) that need to be monitored and how learners and teachers can develop adequate monitoring skills, and (2) the identification of effective regulation strategies, how to develop this repertoire of strategies in teachers and learners, and eventually how to design computer tools for fostering monitoring and regulation skills.

The model is presented in Figure 1. In the model, the monitoring and regulation of both protagonists is centered on the student's performance trace (to be discussed in details in the next section). On the basis of this trace, monitoring involves judging if the information currently attended to is pertinent, that is, if it characterises student's learning. If so, the information is held in working memory and sometimes long-term memory and either kept for oneself or communicated through conversation.

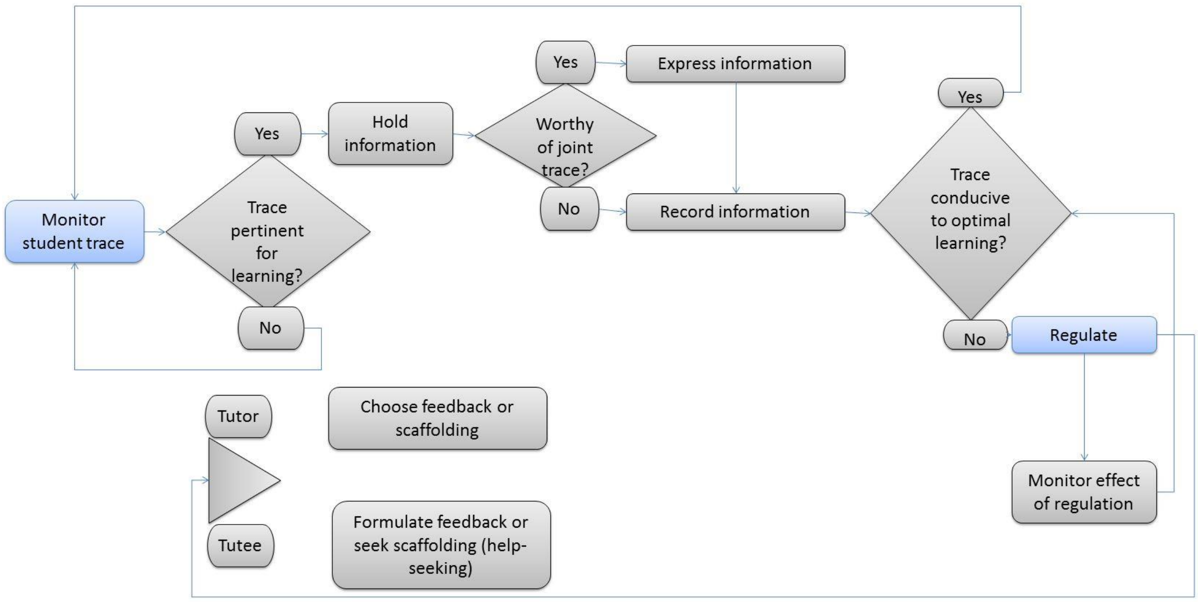

Figure 1. A joint decision-making model of tutoring

The tutor's monitoring includes a specific awareness for important but missing information in the student trace, and as such may involve asking the tutee for information. The recorded information is then used to assess if the current "tutoring state" is both conducive to optimal learning and likely to be maintained. If so, nothing is changed and monitoring continues. If the current tutoring state is reputedly not leading to optimal learning or is likely to shift to another state, one or both protagonists regulate(s) the situation by choosing and enacting a particular move. The effect of the enacted move following a decision is then monitored, in a feedback loop, in which an inefficient move is followed by a different move, and an efficient move brings the agent back to monitoring.

The roles of the actors in this situation are distinguished by the particular moves that they can enact to regulate the interaction. For example, the tutee can formulate self-feedback, select and implement a different problem-solving strategy, or seek help (Karabenick, 2011; Roll et al., 2011; Mercier & Frederiksen, 2008; 2007). The tutor can choose to provide feedback or scaffolding. Types of feedback include providing information about the task, about the processing of the task, about self-regulation, and about the self as a person (Hattie & Timperley, 2007). Scaffolding includes explanations, hints, help with routine tasks, as well as descriptions of procedures and their rationale. This framework shows the information and decisions leading to these moves, and how tutor and tutee moves are sequentially related during the course of a learning interaction. What is missing at this point is an inclusive set of rules specifying the conditions in which the moves previously described must be enacted in order to make sub-optimal tutoring state transition to an optimal one. This work is in line with current research in the field of intelligent tutoring systems (see Chi, et al. (2011a; 2011b) and Muldner & Burleson (2015) for examples), and extends it by considering the role of the tutee in addition to the role of the tutor. The nature of the student trace is discussed next.

The available trace

All theories of learning in a human tutoring context suggest that tutorial decisions should be based on the current needs of the student on the basis of current knowledge level, affective state, and other critical features of the interaction and its context (Collins, Brown & Newman, 1988; D'Mello & Graesser 2010; Vygotsky, 1978; Wood & Wood, 1999). Typically, these theories are not prescriptive at the grain size of the interpersonal interaction between a human tutor and a student, a necessary condition to implement the most appropriate pedagogical tactics through online decision-making (Chi et al. 2011a; 2011b). During a learning task, the student should be active, self-regulated and engaged.

In contrast to this ideal view, Graesser & McNamara (2010), in a presentation of available human tutoring research, concluded that "both the students and human tutors have limited "meta"-knowledge of pedagogy, cognition, communication, emotion, and self-regulated learning" (p. 237). Research has shown that human tutors focus on misconceptions and errors in problem solving. Tutors have limited assessment of the student's cognitive state. They show low likelihood of detecting a student's misconceptions or errors when they occur, and they do not adequately assess a student's global domain expertise. Finally, these authors report that tutors do not implement strategies that are contingent on learner's affective state.

On the other hand, students rely mainly on comprehension monitoring in their efforts to control their learning (Dunlosky & Rawson, 2012). Interestingly, high-knowledge students are more likely to answer no when asked if they understand a specific notion or procedure, because of higher standards of comprehension (Graesser & McNamara, 2010). In addition to comprehension monitoring, students would better control their learning by being aware of critical affective and physiological states, and by making decisions on this basis, such as a decision to disengage from a learning effort (Efklides, 2011). Cognitive and affective processes during a learning episode are increasingly understood as highly intertwined, and should be studied concomitantly using recent models of self-regulated learning, such as Efklides' (2011) MASRL model.

In summary, tutoring is a highly interactive mode of learning in which the tutor and the tutee makes numerous decisions on a moment-by-moment basis about the course of actions in a highly dynamic and information-rich situation. The efficacy of tutoring rests on the joint agency of the protagonists towards the provision of feedback and scaffolding that is maximally aligned with the learning needs of the tutee. In this context, the required information concerns both cognitive and affective processes and cannot be obtained completely from conversation and the observation of behaviors. Psychophysiological measurement, in an approach compatible with the natural tutoring interaction, can help lower this deficit in information.

Monitoring and regulating the behavioral and psychophysiological signature of a tutoring interaction

It was shown previously that a minimal conceptual frame should provide sufficient theoretical foundations for an educational neuroscience research program on tutoring. Concerning the proposed integration of new approaches in a field of research with a long tradition, Hyöna (2010) asserts that methodological innovations contribute in a very significant way to the advancement of science. This may be particularly true at this time for the use of electroencephalography (EEG) in an educational neuroscience perspective on tutoring research. Recent methodological and technological advances in cognitive neuroscience, taken together, should make studies along these lines possible, as discussed next. In any case, the use of EEG in educational neuroscience has to be complemented with pertinent behavioral data, a case previously made in the use of eye-tracking methodology (Hyöna, 2010).

As envisioned in this essay, the near future of educational neuroscience research on tutoring rests mainly on dense-array EEG. “The combination of high resolution EEG, modern inverse solution approaches, realistic head shape models, and proper post-processing techniques are already leading to the use of EEG as a true neuroimaging procedure” (Michel et al., 2004, p.2215). Current developments in the methods of source analysis allows one to consider temporal and spatial dimension of brain activity simultaneously and brings EEG at the forefront of contemporary neuroimaging methods with a combined high spatial and temporal resolution (Dalal et al., 2011). Above all, EEG allows for measurement under minimal restraints (Lee & Ng, 2011) and in interactive settings (Koike, Tanabe & Sadato, in press), making it possible to reproduce key features of authentic learning environments in the laboratory. Recent analysis techniques of dual-EEG, that is, EEG on two people in interaction, have revealed properties of brain functioning in the context of interpersonal interactions that may complement behavioral indicators (Di Paolo & De Jaegher, 2012). EEG caps are worn by the participant as any form of headwear, whereas in a MRI study, the participant is positioned in the machine which surrounds her and must be completely immobile for the entire duration of the experiment. The higher tolerance for movement of EEG enables the participants to sit in front of a computer, manipulate artifacts, use pencils, have face-to-face conversation, and even move within a room when using wireless EEG equipment. Threats to data integrity in EEG, such as excessive head movements and facial muscular activity, affect only the portion of the signal acquired during those events and procedures may effectively be used to minimize their impact on the quality of the data in the time-frequency approach. The proof of concept of this approach is discussed next in light of two relatively advanced lines of research which can serve as illustrations: cognitive load and affect.

Cognitive load is a major determinant of learning in problem-solving situations such as those used in tutoring. Three types of cognitive load apply to learning (Antonenko et al., 2010). Intrinsic load refers to the complexity of the content in terms of concurrently interacting chunks of information in a learner’s working memory, and is modulated notably by the learner’s prior knowledge of the domain. The two other types, germane and extraneous cognitive load, are related to the design of the learning task (Verhoeven, Schnotz & Pass, 2009). Germane load is desirable and associated with cognitive operations necessary or conducive to learning, whereas extraneous load is unwanted and associated with cognitive operations required by the situation that are not conducive to learning, and which result from bad pedagogical design or sub-optimal learner regulation. Even if research on cognitive load has mainly examined the presentation of information in learning situations such as hypermedia and multimedia, cognitive load theory may apply to highly dynamic situations in which there is a bidirectional exchange of information between a tutor and a learner. Although the impact of cognitive load on learning is best understood on a moment-to-moment basis (Kalyuga, 2011), the construct is customarily measured at relatively long intervals using retrospective self-reports, which have been shown to provide limited and imprecise measures (Matthews et al., 2015); van Gog et al., 2012). Instantaneous cognitive load, that is, how cognitive load fluctuates every moment during a task, is the cornerstone of the measurement of this construct, because many other indices are derived from it for a given learning episode; these include peak load (maximum instantaneous load), average load (mean instantaneous load), and accumulated load (total amount of load) (Antonenko et al., 2010). By definition, the precision of the instantaneous cognitive load index is related to the temporal resolution of the measure. Psychophysiological measurements typically provide information hundreds of times every second, which is then aggregated and eventually indexed with contextual cues.

Work in neuroergonomics, the field concerned with using psychophysiological measures to address issues of human performance in real-world tasks, has led to validated and robust measures of cognitive load based on electroencephalography (EEG) in authentic contexts (Antonenko et al., 2010). Moreover, low-resolution and relatively inexpensive EEG systems provide reasonable estimates using proprietary algorithms, such as BIOPAC B-alert X10 system, which provides a probability of high and low cognitive load for each one-second interval (Berka et al., 2004; Mercier et al., 2012). Indexes of cognitive load can also be computed on the basis of EEG signal obtained using any equipment, as ratios of power spectral density in given frequency bands at specific sites, an approach known as spectral analysis (Berka et al., 2004). Measurement of instantaneous cognitive load using EEG, or any other method, provides estimates of cognitive load in which intrinsic, germane and extraneous components cannot be differentiated. Thus, the formulation of cognitive load as three components in educational contexts rely on the analysis of the learning situation to determine how they contribute to overall cognitive load, and as such, the dynamic measurement must be interpreted in terms of the changing context of the learning task and the support provided (Sweller, Ayres & Kalyuga, 2011). The use of high-resolution EEG with time-varying cortical connectivity estimation techniques (see Astolfi et al., 2010) may help characterize cognitive load by showing the patterns of activation between areas associated with the processing of different sensory inputs.

Recent developments in educational research tend to reaffirm that affects are playing a crucial role in learning by showing dynamic links between emotions and cognition (Patten, 2011). In her model, Patten distinguishes between dispositions, basic emotions and feelings. Dispositions may be understood as the mood, are largely unconscious, and are basic to survival. Basic emotions are instinctive and include happiness, sadness, fear, anger, disgust and surprise. Feelings are conscious and involve a cognitive analysis of somatic patterns or associations between such somatic patterns and objects or events. Affective states are important determinants of learning since they influence the planning and conduct of cognitive behavior through executive functions.

However, research on cognition and research on emotions have traditionally been conducted in relative isolation, leading to a lack of understanding of how cognition and emotions interact dynamically during learning. Whereas convincing methodology for the study of cognition emerged decades ago (Newell & Simon, 1972), measuring emotions in a relatively good temporal resolution has remained impractical until recently. Psychophysiological methods from affective neuroscience and methodologies from affective computing may prove instrumental in bridging this gap between self-report measures and variations in affective states since they can measure correlates of emotions as they unfold over time, and those correlates can be matched with records of concurrent cognitive processes and indexed with contextual features of the learning environment (Immordino-Yang, 2011; Kukolja et al., 2014). A review of experimental research by Kreibig (2012) revealed how ambiguous psychophysiological responses to emotional stimuli can be, in sharp discontinuity with the contrasting range of emotions a person can experience, even in educational contexts (see Pekrun, 2010). While experimental paradigms focused on short-term changes may be difficult to reinvest in the study of natural interactions, Stikic et al. (2014) showed that continuous EEG can be used to classify emotions as positive and negative. Their study suggests that a probabilistic estimation of positive and negative affect can be derived reliably for two-minute episodes, which are indexed on the basis of thematic shifts within a 19-minute narrative story. Thus, recent research suggests that a multi-channel approach to the temporally fine-grained measurement of emotions is necessary, but applied outcomes may require substantial basic research. In this regard, Azcarraga & Suarez (2013) found that the classification of learners' academic emotions on the basis of EEG data in the context of a math learning software was substantially increased by including a trace of the mouse behavior.

Whereas subjects' limited ability to self-report and self-express motivation and the practical challenges of measurement of changes in motivation during learning activities are widely recognized, psychophysiological approaches may be key in interpreting emotional states, especially as they are thought to transition even faster than cognitive states during the performance of a learning task, and may often not be amenable to conscious recognition (Fulmer & Frijters, 2009). According to this author, these measures are highly context-specific, but may be subject to confounding factors. Pupil size (Fulmer & Frijters, 2009), heart rate variability (Riganello, Garbarino & Sannita, 2012), EEG patterns both from spectral analysis (Wyczesany, Kaiser & Coenen, 2010) and Event-Related Potentials (Zhang, Zhou & Oei, 2011) approaches, skin conductance (Fulmer & Frijters, 2009) are correlates of affective states. The interpretation of psychophysiological data is related to positive and negative emotional states related to pleasantness (valence), as well as the sense of mobilization or activation (arousal) (Gomez et al., 2009). Valence influences attention, aspects of thinking, and memory (Patten, 2011). Indicators of motivation, interest, and engagement can be derived from combinations of these indexes.

The study of motivation and interest from a psychophysiological approach has traditionally focused on simple motivations associated with biological needs, but recent research concerns more complex human motivations, such as those involved in cognitive task performance (Fulmer & Frijters, 2009) and learning (Afzal & Robinson, 2011). New conceptualizations related to motivation and interest include flow during learning (Joo, Joung & Kim, 2014) and feeling of presence in virtual environments (Clemente et al., 2013), and it can be suggested that both concepts can be fruitfully explored in tutoring research. Although the development of interest involves a progression through four phases (Hidi & Renninger, 2006), data from affective neuroscience cannot discriminate between them or signal transitions on a moment-to-moment basis: those stages involve the same psychophysiological signature. The possibility of extracting this information from those measures over long periods of time is an open question. Interest is related to engagement: continued engagement is necessary for interest. Pope, Bogart, and Bartolome (1996) defined engagement as a combination of attention and arousal and includes processes involving information-gathering, visual scanning and sustained attention (Freeman et al., 2004; Poythress et al., 2006; Stevens, Galloway & Berka, 2007). Engagement and cognitive load are reliable predictors of short-term success in mathematics problem solving (Galan & Beal, 2012). Distraction is a notion of the subject's being involved somewhere other than the cognitive tasks of interest. Distraction can involve instances of frustration, boredom or confusion (Poythress et al., 2006). Other EEG correlates of engagement include distraction and drowsiness (Berka et al., 2004).

Globally, the strategy for the analysis data of this kind should be oriented towards discrete and time-stamped events. Such an approach has been used in cognitive science for decades, notably in the analysis of think-aloud protocols (Ericsson & Fox, 2011) and conversation analysis (Delium, 2003). An analytical approach based on the sequential dependency of discrete states is pivotal in the development of educationally-relevant research in educational neuroscience. Establishing causality – the notion that an instructional context produces learning gains - has always been a challenge in education, but a focus on learning trajectories may contribute significant insights in this respect. By studying antecedent-consequent relationships between discrete events (that is, their temporal causality), this approach capitalizes on the definition of causality in which a cause always precedes its effect (Pearl, 2000). In a domain in which processes unfold rapidly in time, temporal causality may surpass experimental causality in its potential for practical implications. Temporal causality can capture the effects of fast-occurring events, isolated or in specific combinations, whereas experimental causality can only be established for situations that can be manipulated experimentally, thereby losing in temporal resolution and/or ecological validity. Rooted in information theory, sequential analysis (Gottman & Roy, 1990) will be instrumental in discovering sequential dependency and co-occurrence of educationally-relevant psychophysiological, cognitive, and social processes. Notions from chaos theory and dynamic systems theory (see Arrow, McGrath & Berdahl, 2000) refine the analysis of adjacent and lagged antecedent-consequent (unigrams, digrams, trigrams, etc). In fact, within this approach, the challenge resides mainly in the transformation of the EEG signal into meaningful discrete events. Three approaches currently exist: brain microstates, spectral analysis, and event-related potentials.

Spectral analysis is another pivotal strategy in the proposed research, as it is related to activation of brain regions over relatively long periods of time. For example, it has been found that the phase pattern of Theta band (4–8 Hz) responses recorded from human auditory cortex reliably tracked and discriminated spoken sentences (Goswami, 2011). Our own experiments with the B-Alert system have led to encouraging news accompanied by many challenges. Nolte & Müller (2010) provide indications regarding how causality can be estimated using a three-step data-analysis methodology (PISA, MOCA, and PSI), using dense-array EEG (simulation data with 118 channels). The cognitive states inferred from power ratios in specific frequency bands can be segmented temporally into discrete states, and amenable to the analytical strategies put forward here. In order to do this, the EEG data has to be synchronized with behavioral data and indexed with mutually exclusive categories emanating from these data. However, the potential for causal explanations in sequence-oriented analysis is severely impaired by the grain size of the synchronization of the data (Mercier et al., 2012).

Conclusion: Increasing the optimization of learning through greater contingency in tutoring

The elements discussed throughout this text will help frame research questions aiming at determining the unique contributions from electrophysiological measures emanating from cognitive and affective neuroscience. Indeed, the major argument put forward in this paper is that in principle, the consideration of time scales faster than speech and elements outside the realm of conscious verbalization represents a major advance for tutoring research and that to this end, electrophysiological measures are necessary. By incorporating the psychophysiological level, educational neuroscience may be key in resolving the temporal and phenomenological indetermination of cognitive behavioral data. In line with Kelly's (2011) contention (see also Devonshire & Dommett, 2010), it can be suggested that theoretical claims about the efficacy of tutoring that remain ambiguous at the behavioral level will be further tested by hypothesis testing at the level of mechanism, the psychophysiological level. Such claims are related to the interaction granularity hypothesis (VanLehn, 2011). The learning gains depend largely on the decisions of the agents in a tutoring situation, understood as self-, other- or co-regulation depending on the tutoring context. The learner, the tutor, or even the ITS can make better decisions if provided with additional pertinent information about the tutorial interaction and its outcomes. While the argument put forward seems to hold in principle in light of current research, empirical results are necessary to show the benefits of the proposed approach. Experiments coupling electrophysiological measures with behavioral information must be conducted to demonstrate if and how the EEG for example can provide additional or better information than behavioral information alone. If our proposition holds its ground empirically, the next question should be related to the use of this information. Can the tutor and/or learner benefit from additional information, and then how and when should it be presented?

The next step in the proposed research involves the further development of a conceptualization of learning as a series of events (Kapur, 2011). This can be facilitated by the joint consideration of the psychophysiological, cognitive, and social levels, but can proceed productively at a given level, following research traditions in the study of individual cognition during learning and in the study of a learning interaction. From an empirical point of view, challenges abound, but they should not be seen as pitfalls. It seems prudent to begin the projected studies with trials without speech and minimal movement, but recent improvements in decontamination procedures of the EEG signal may provide opportunities to study more natural interactions (Gevins, Chan & Sam-Vargas, 2012). It should be noted that EEG data is contaminated even in the most controlled circumstances. "Eye blinks, eye movements, muscle activity in the vicinity of the head (e.g. face muscles, jaws, tongue, neck), heartbeat, pulse and Mayer waves are examples of physiological artifact sources" (Winkler, Haufe & Tangermann, 2011, p. 1), and are the most important source of measurement error (Luu et al., 2009). Any authentic learning situation abounds in all these sources of noise and currently represents a stimulating context for the scientist in educational neuroscience but a challenge for the cognitive neuroscientist. EEG signatures should be studied with geodesic, whole-head nets and powerful decontamination algorithms developed. Whatever its source, noise in the signal obtained with quality equipment is not random and can be detected by appropriate algorithms. One such fully automated algorithm, based on Independent Component Analysis, has been developed by Winkler, Haufe & Tangermann (2011). It was developed using dense-array EEG (121 channels) in an auditory response-time task and in an auditory ERP task, and has been shown to be robust enough for continuous signal decontamination, such as Brain-Computer Interface applications. Dana analysis techniques are sufficient: they have to be fully exploited to their full potential with respect to the goals of educational neuroscience. Learning domains such as reading and mathematics have already been substantially researched in cognitive neuroscience (Ansari, Coch & De Smedt, 2011; Ansari, De Smedt & Grabner, 2012; Byrnes, 2012; Houdé et al., 2011; Kelly, 2011; Lee & Ng, 2011; van Nes, 2011), with a strong emphasis on learning disabilities (Byrnes, 2012), and domains associated with bilingualism (Pettito, 2009), either the acquisition of a second language (Koizumi, 2011) or learning school subjects in multiple languages (Grabner, Saalbach & Eckstein, 2012) are emerging so they may represent facilitating contexts for empirical trials. Moreover, tutoring in these domains is typical in practice.

The goal of this essay was to provide a sufficient, albeit certainly partial synthesis of recent developments in tutoring research and research in affective and cognitive neuroscience both from a theoretical and methodological perspective to highlight the possibilities and challenges of educational neuroscience from the point of view of a specific field of educational research. Through the discussion about the study of tutoring, it is our contention that these elements should be paradigmatic of the field. Moreover, it is argued as a final point that the field should tackle a pivotal question: what is the psychophysiological signature of learning in authentic contexts? This signature, called empirical primitives are becoming known via cognitive neuroscience-based analyses (Kelly, 2011; Koike, Tanabe & Sadato, in press). Elements of answer to this question can emanate from a careful, thoughtful and patient use of the framework proposed before. A minimal answer will require substantial research, but the theoretical and practical leaps are incommensurate, in the sense that indicators of learning within time frames, permitting strong temporal causality, would become the variables of choice for researchers in educational neuroscience. It is becoming clear that cognitive research, as the basis of behavioral data shows, cannot by itself provide this answer. To answer this pivotal question for the field, the observational-correlational-experimental loop strategy (Kelly, 2011) has to be used, in which the first stages concern model building and the last stage represents model testing.

Many other questions can be examined. During the course of a tutorial interaction, to what extent is the tutor able to perceive the emotional and cognitive state of the learner? Do what extent is the scaffolding and feedback provided appropriate? Are there differences between expert and novice tutors? During a tutor's explanations to a tutee, do expert and novice tutors perceive student cognitive overload, or disengagement as efficiently? To what extent are those processes amenable to monitoring and regulation by the student and the tutor? Monitoring can also be extended to the tutor. In this context, what is the relationship between tutor's cognitive and affective processes and the appropriateness of the scaffolding and feedback provided to the student?

The psychophysiological information gained from continuous measures during a learning interaction can be used in three ways. Firstly, this information can provide a new kind of evidence in the study of the effects of particular feedback and scaffolding strategies. Secondly, this information can be used in constructing a tutoring efficacy monitoring tool after the tutoring session. Thirdly, this information can be used in constructing a monitoring tool during a tutoring session. As an online monitoring tool, two variations can be envisioned: available to the tutor only, or to the tutor and the tutee. The technology has been recently made available, but careful theorizing and testing are required to put it to good use during tutorial interactions.

Psychophysiological information can be used to provide tools to help harness and instantiate the typically vast pedagogical knowledge of human tutors by capitalizing on their sensitivity to context. It can also be integrated with other types of data contributing to the "student model" on which an intelligent tutoring system makes pedagogical decisions. This information could be used to create a decision model of "psychophysiologically-enhanced" tutoring. The availability of extremely simple and affordable EEG equipment, including for example a system measuring brain activity at only one site on the scalp which can discriminate with 86% accuracy between a neutral and attentive cognitive state, makes such use in schools a realistic possibility (Mostow, Chang & Nelson, 2011). Taking the context into account could potentially provide an answer to important questions such as: is the scaffolding helping the student to learn from the problem or only to solve the problem (Hmelo & Day, 1999)? In itself, the notion of scaffolding requires the identification of the nature of the guidance and of the knowledge learned. Tutors and students may be surprised at how much information regarding learning processes is concealed, make associations between psychophysiological information and behavioral manifestations, and become more aware of conditions conductive to learning, and consequently strive to attain and maintain these conditions. Ultimately, this line of work may represent a potent vector empowering the students and tutors, and as such may embody one of the most desirable outcomes of educational neuroscience (Ferrari, 2011).

Acknowledgements

The authors would like to thank the editors of the journal and two anonymous reviewers for their constructive and inspiring feedback and suggestions on an earlier version of this manuscript.

References

Afzal, S., & Robinson, P. (2011). Designing for automatic affect inference in learning environments. *Educational Technology & Society*, 14(4), 21–34.

Anderson, J.R. (2002). Spanning seven orders of magnitude: A challenge for cognitive modeling. *Cognitive Science*, 26, 85-112.

Aleven, V., McLaren, B.M., Sewall, J., & Koedinger, K.R. (2009). A new paradigm for intelligent tutoring systems: Example-tracing tutors. *International Journal of Artificial Intelligence in Education*, 19, 105-154.

Aleven, V., Stahl, E., Schworm, S., Fischer, F., & Wallace, R. (2003). Help seeking and help design in interactive learning environments. *Review of Educational Research*, 73(3), 277-320.

Ansari, D., Coch, D., & De Smedt, B. (2011). Connecting education and cognitive neuroscience: Where will the journey take us? *Educational Philosophy and Theory*, 43(1), 37-42.

Ansari, D., De Smedt, D., & Grabner, R.H. (2012). Neuroeducation – A critical overview of an emerging field. *Neuroethics*, 5, 105-117.

Antonenko, P., Paas, F., Garbner, R., & van Gog, T. (2010). Using electroencephalography (EEG) to measure cognitive load. *Educational Psychology Review*, 22, 425–438.

Arrow, H., McGrath, J.E., & Berdahl, J.L. (2000). *Small Groups as Complex Systems*. Thousand Oaks, CA: Sage Publications Inc.

Astolfi, Cincotti, F., Mattia, D., De Vico Fallani, F., Vecciato, G., Salinari, S., Vecciato, G., Witte, H., & Babiloni, F. (2010). Time-varying cortical connectivity estimation from noninvasive, high-resolution EEG recordings. *Journal of Psychophysiology*, 24(2), 83–90.

Azcarraga, J., & Suarez, M.T. (2013). Recognizing student emotions using brainwaves and mouse behavior data. *International Journal of Distance Education Technologies*, 11(2), 1-15.

Berka, C., Levendowski, D.J., Cvetinovic, M.M., Petrovic, M.M., Davis, G., Lumicao, M.N., Zivkovic, V.T., Popovic, M.V., & Olmstead, R. (2004). Real-time analysis of EEG indexes of alertness, cognition and memory acquired with a wireless EEG headset. *International Journal of Human-Computer Interaction*, 17(2), 151-170.

Boyer, K.E., Phillips, R., Ingram, A., Young Ha, E., Wallis, M., Vouk, M., & Lester, J. (2011). Investigating the relationship between dialogue structure and tutoring effectiveness: A hidden Markov modeling approach. *International Journal of Artificial Intelligence in Education*, 21, 65–81.

Byrnes, J.P. (2012). How neuroscience contributes to our understanding of learning and development in typically developing and special-needs students. In K. R. Harris, S. Graham, T. Urdan, C.B. McCormick, G. M. Sinatra & J. Sweller (Eds.), *APA educational psychology handbook, Theories, constructs, and critical issues* (Vol. 1, pp. 561-595). Washington, DC, US: American Psychological Association.

Chi, M., VanLehn, K., Litman, D., & Jordan, P. (2011a). Empirically evaluating the application of reinforcement learning to the induction of effective and adaptive pedagogical strategies. *User Model User-Adapted Interaction*, 21, 137–180.

Chi, M., VanLehn, K., Litman, D., & Jordan, P. (2011b). An evaluation of pedagogical tutorial tactics for a natural language tutoring system: A reinforcement learning approach. *International Journal of Artificial Intelligence in Education*, 21, 83–113.

Chi, M.T.H., Siler, S.A., Jeong, H., Yamauchi, T., & Hausmann, R.G. (2001). Learning from human tutoring. *Cognitive Science*, 25, 471-533.

Clemente, M., Rodríguez, A. Rey, B., & Alcañiz, M. (2013). Measuring presence during the navigation in a virtual environment using EEG. *Annual Review of CyberTherapy and Telemedicine*, 11, 136-140.

Collins, A., Brown, J.S., & Newman, S.E. (1988). Cognitive apprenticeship: Teaching the crafts of reading and mathematics. In L.B. Resnick (Ed.), *Knowing, learning and instruction: Essays in honor of Robert Glaser* (pp. 453-494). Hillsdale, NJ: Laurence Erlbaum Associates.

Dalal, S.S., Zumer, J.M., Guggisberg, A.G., Trumpis, M., Wong, D.D.E., Sekihara, K., & Nagarajan, S.S. (2011). MEG/EEG source reconstruction, statistical evaluation, and visualization with NUTMEG. *Computational Intelligence and Neuroscience*, Art. 758953. doi:10.1155/2011/758973

Dekker, S., Lee, N.C., Howard-Jones, P., & Jolles, J. (2012). Neuromyths in education: Prevalence and predictors of misconceptions among teachers. *Frontiers in Psychology*, 3, 1-8.

Delium, C. (2003). OSCAR, un environnement de communication médiatisée structurée par les actes de langage. In C. Desmoulins, P. Marquet et D. Bouhineau (dir.), *Proceedings EIAH 2003* (pp. 127-138). Paris : INRP.

Devonshire, I.M, & Dommett, E.J. (2010). Neuroscience: Viable applications in education? *Neuroscientist*, 16, 349-356.

Di Paolo, E., & De Jaegher, H. (2012). The interactive brain hypothesis. *Frontiers in Human Neuroscience*, 6, 1-16.

D'Mello, S.K., & Graesser, A. (2010). Multimodal semi-automated affect detection from conversational cues, gross body language, and facial features. *User Model User-Adapted Interaction*, 20,147–187.

Dunlosky, J., & Rawson, K.A. (2012). Overconfidence produces underachievement: Inaccurate self-evaluations undermine students' learning and retention. *Learning and Instruction*, 22, 271-280.

Efklides, A. (2011). Interactions of metacognition with motivation and affect in self-regulated learning: The MASRL model. *Educational Psychologist*, 46(1), 6-25.

Ericsson, K. A., & Fox M.C. (2011). Thinking aloud is not a form of introspection but a qualitatively different methodology: Reply to schooler. *Psychological Bulletin*, 137(2), 351–354.

Ferrari, M. (2011). What can neuroscience bring to education? *Educational Philosophy and Theory*, 43(1), 31-36.

Frederiksen, C. H., Roy, M., & Bédard, D. (1995). Discourse processing in situated cognition: Learning through tutorial dialogue in complex domains. In J.D. Moore & J.F. Lehman (Eds.), *Proceedings of the 17th Annual Conference of the Cognitive Science Society* (pp. 643–647). Hillsdale, NJ: Erlbaum.

Freeman, F.G., Mikulka, P.J., Scerbo, M.W., & Scott, L. (2004). An evaluation of an adaptive automation system using a cognitive vigilance task. *Biological Psychology*, 67, 283–297.

Fulmer, S.M., & Frijters, J.C. (2009). A review of self-report and alternative approaches in the measurement of student motivation. *Educational Psychology Review*, 21, 219–246.

Galan, F.C., & Beal, C.R. (2012). EEG estimates of engagement and cognitive workload predict math problem solving outcomes. *Lecture Notes in Computer Science*, 7379, 51-62.

Gevins, A., Chan, C.S., & Sam-Vargas, L. (2012). Towards measuring brain function on groups of people in the real world. *PLoS ONE*, 7(9), 1-9.

Gobet, F., & Wood, D. J. (1999). Expertise models of learning and computer-based tutoring. *Computers & Education*, 33, 189-207.

Gomez, P., Zimmermann, P.G., Schär, S.G., & Danuser, B. (2009). Valence lasts longer than arousal: Persistence of induced moods as assessed by psychophysiological measures. *Journal of Psychophysiology*, 23(1), 7–17.

Grabner, R.H., Saalbach, H., & Eckstein, D. (2012). Language-switching costs in bilingual mathematics learning. *Mind, Brain, & Education*, 6(3), 147-155.

Graesser, A.C., Bowers, C., Hacker, D.J., & Person, N. (1997). An anatomy of naturalistic tutoring. In K. Hogan & M. Pressley (Eds.) *Scaffolding student learning: Instructional approaches and issues. Advances in learning & teaching* (pp. 108-144). Cambridge, MA, US: Brookline Books.

Graesser, A., & McNamara, D. (2010). Self-regulated learning in learning environments with pedagogical agents that interact in natural language. *Educational Psychologist*, 45(4), 234-244.

Goswami, U. (2011). Educational neuroscience: Developmental mechanisms: Towards a conceptual framework. *NeuroImage*, 57, 651–658.

Gottman, J. M., & Roy, A. K. (1990). *Sequential analysis: A guide for behavioral researchers*. NY: Cambridge University Press.

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research*, 77(1), 81-112.

Hidi, S., & Renninger, K.A. (2006). The four-phase model of interest development. *Educational Psychologist*, 41(2), 111-127.

Hmelo, C., & Day, R. (1999). Contextualized questioning to scaffold learning from simulations. *Computers & Education*, 32, 151-164.

Houdé, O., Pineau, A., Leroux, G., Poirel, N., Perchey, G., Lanoë, C., Lubin, A., Turbelin, M.R., Rossi, S., Simon, G., Delcroix, N., Lamberton, F., Vigneau, M., Wisniewski, G., Vicet, J.R., & Mazoyer, B. (2011). Functional magnetic resonance imaging study of Piaget's conservation-of-number task in preschool and school-age children: A neo-Piagetian approach. *Journal of Experimental Child Psychology*, 110, 332–346.

Hyöna, J. (2010). The use of eye movements in the study of multimedia learning. *Learning and Instruction*, 20, 172-176.

Immordino-Yang, M.H. (2011). Implications of affective and social neuroscience for educational theory. *Educational Philosophy and Theory*, 43(1), 98-103.

Järvelä S., & Hadwin, A.F. (2013). New frontiers: Regulating learning in CSCL. *Educational Psychologist*, 48(1), 25–39.

Joo, Y.J., Joung, S., & Kim, J. (2014). Structural relationships among self-regulated learning, learning flow, satisfaction, and learning persistence in cyber universities. *Interactive Learning Environments*, 22(6), 752-770.

Kalyuga, S. (2011). Cognitive Load Theory: Implications for affective computing. In P.M. McCarthy & C. Murray (Eds.), *Proceedings of the Twenty-Fourth International Florida Artificial Intelligence Research Society Conference* (pp. 105-110). Florida: AAAI Publications.

Kapur, M. (2011). Temporality matters: Advancing a method for analyzing problem-solving processes in a computer-supported collaborative environment. *Computer-Supported Collaborative Learning*, 6, 39–56.

Karabenick, S.A. (2011). Classroom and technology-supported help seeking: The need for converging research paradigms. *Learning and Instruction*, 21, 290-296.

Kelly, A.E. (2011). Can cognitive neuroscience ground a science of learning? *Educational Philosophy and Theory*, 43(1), 17-23.

Kim, M.C., & Hannafin, M.J. (2011). Scaffolding problem solving in technology-enhanced learning environments (TELEs): Bridging research and theory with practice. *Computers & Education*, 56, 403–417.

Koike, T., Tanabe, H.C., & Sadato, N. (in press). Hyperscanning neuroimaging technique to reveal the "two-in-one" system in social interactions. *Neuroscience Research.*

Koizumi, H. (2011). Brain-science based cohort studies. *Educational Philosophy and Theory*, 43(1), 48-55.

Kukolja, D., Popovic, S., Horvat, M., Kovac, B., & Cosic, K. (2014). Comparative analysis of emotion estimation methods based on physiological measurements for real-time applications. *International Journal of Human-Computer Studies*, 72, 717–727.

Kreibig, S.D. (2010). Autonomic nervous system activity in emotion: a review. *Biological Psychology*, 84, 394–421.

Lee, K. & Ng, S.F. (2011). Neuroscience and the teaching of mathematics. *Educational Philosophy and Theory*, 43(1), 48-55.

Luu, P., Frank, R., Kerick, S., & Tucker, D.M. (2009). Directed components analysis: An analytic method for the removal of biophysical artifacts from EEG data. In D.D. Schmorrow & C.M. Fidopiastis (Eds.), *Augmented Cognition. Neurocognition and Machine Learning* (pp. 411–416). Berlin, Heidelberg: Springer.

Matthews, G., Reinerman-Jones, L.E., Barber, D.J., & Abich, J. (2015). The psychometrics of mental workload: Multiple measures are sensitive but divergent. *Human Factors*, 57(1), 125–143.

Mercier, J., & Frederiksen, C.H. (2007). Individual differences in graduate students' help-seeking process in using a computer coach in problem-based learning. *Learning and Instruction*, 17, 184-203.

Mercier, J., & Frederiksen, C.H. (2008). The structure of the help-seeking process in using a computer coach in problem-based learning. *Computers & Education*, 51(1), 17-33.

Mercier, J., Léger, P.M., Girard, C., & Dion, J.S. (2012). Bridging the gap between cognitive neuroscience and education: Psychophysiological and behavioral data collection in authentic contexts. *Neuroeducation*, 1(1), 5-28.

Michel, M.C., Murray M.M., Lantz G., Gonzalez, S., Spinelli, L., & Grave de Peralta, R. (2004). EEG source imaging. *Clinical Neuphysiology*, 115, 2195-2222.

Mostow, J., Chang, K., & Nelson, J. (2011). Toward Exploiting EEG Input in a Reading Tutor. In G. Biswas, S. Bull, J. Kay, A. Mitrovic (Eds.), *Lecture Notes in Computer Science*, 6738 (pp. 230–237). Berlin, Heidelberg: Springer.

Muldner, K., & Burleson, W. (2015). Utilizing sensor data to model students' creativity in a digital environment. *Computers in Human Behavior*, 42, 127–137.

Newell, A. (1990). *Unified theories of cognition*. Cambridge, Mass: Harvard University Press.

Newell, A., & Simon, H.T. (1972). *Human problem solving*. UK: Prentice Hall.

Nolte, G., & Müller, K.R. (2010). Localizing and estimating causal relations of interacting brain rhythms. *Frontiers in Human Neuroscience*, 4, 1-5.

Panadero, E., & Järvelä, S. (2015). Socially shared regulation of learning: A review. *European Psychologist*, 20, 190-203.

Patten, K.E. (2011). The somatic appraisal model of affect: Paradigm for educational neuroscience and neuropedagogy. *Educational Philosophy and Theory*, 43(1), 87-97.

Pearl, J. (2000). *Causality: Models, Reasoning, and Inference*. Cambridge: Cambridge University Press.

Pettito, L.A. (2009). New discoveries from the bilingual brain and mind across the life span: Implications for education. *Mind, Brain, & Education*, 3(4), 185-197.

Pope, A.T., Bogart, E.H., & Bartolome, D.S. (1996). Biocybernetic system evaluates indices of operator engagement in automated task. *Biological Psychology*, 40, 187-195.

Poythress, M., Russell, C., Siegel, S., Tremoulet, P.D., Craven, P., Berka, C., Levendowski, D.J., Chang, D., Baskin, A., Champney, R., Hale, K., & Milham, L. (2006). *Correlation between Expected Workload and EEG Indices of Cognitive Workload and Task Engagement*. Research Report. Retrieved October 6, 2017, from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.525.3018&rep=rep1&type=pdf.

Pratt, M. W., & Savoy-Levine, K. M. (1998). Contingent tutoring of long-division skills in fourth and fifth graders: Experimental tests of some hypotheses about scaffolding. *Journal of Applied Developmental Psychology*, 19, 287–304.

Riganello, F., Garbarino, S., & Sannita, W.G. (2012). Heart rate variability, homeostasis, and brain function a tutorial and review of application. *Journal of Psychophysiology*, 26(4), 178–203.

Roll, I., Aleven, V., McLaren, B.M., & Koedinger, K.R. (2011). Improving students' help-seeking skills using metacognitive feedback in an intelligent tutoring system. *Learning and Instruction*, 21, 267-280.

Stevens, R.H., Galloway, T.L., Wang, P., & Berka, C. (2011). Cognitive neurophysiologic synchronies: What can they contribute to the study of teamwork? *Human Factors*, 54(4), 489-502.

Stikic, M., Berka, C., Levendowski, D.J., Rubio, R.F., Tan, V., Korszen, S., Barba, D., & Wurzer, D. (2014). Modeling temporal sequences of cognitive state changes based on a combination of EEG engagement EEG workload and heart rate metrics. *Frontiers in Neuroscience*, 8, 342.

Sweller, J., Ayres, P., & Kalyuga, S. (2011). *Cognitive load theory*. Berlin, Heidelberg: Springer.

van Gog, T., Kirschner, F., Kester, L., & Paas, F. (2012). Timing and frequency of mental effort measurement: Evidence in favour of repeated measures. *Applied Cognitive Psychology*, 26, 833–839.

van de Pol, J., Volman, M., & Beishuizen, V.J. (2011). Patterns of contingent teaching in teacher-student interaction. *Learning and Instruction*, 21, 46-57.

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist*, 46(4), 197-221.

van Nes, F. (2011). Mathematics education and neurosciences: Towards interdisciplinary insights into the development of young children's mathematical abilities. *Educational Philosophy and Theory*, 43(1), 75-80.

Verhoeven, L., Schnotz, W., & Pass, F. (2009). Cognitive load in interactive knowledge construction. *Learning and Instruction*, 19, 369-375.

Volet, S., Vauras, M., & Salonen, P. (2009). Self- and social regulation in learning contexts: An integrative perspective. *Educational Psychologist*, 44(4), 215–226.

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Cambridge: Harvard University Press.

Winkler, I., Haufe, S., & Tangermann, M. (2011). Automatic classification of artifactual ICA components for artifact removal in EEG signals. *Behavioral and Brain Functions*, 7(30), 1-15.

Wood, D., Bruner, J., & Ross, G. (1976). The role of tutoring in problem solving. *Journal of Child Psychology and Psychiatry*, 17, 89-100.

Wood, H., & Wood, D. (1999). Help seeking, learning and contingent tutoring. *Computers & Education*, 33, 153-169.

Wyczesany, M., Kaiser, J., & Coenen, A.M.L. (2010). Associations between self-report of emotional state and the EEG patterns in affective disorders patients. *Journal of Psychophysiology*, 24(1), 33–40.

Zhang, J., Zhou, R., & Oei, T.P.S. (2011). The effects of valence and arousal on hemispheric asymmetry of emotion evidence from event-related potentials. *Journal of Psychophysiology*, 25(2), 95–103.

To cite this article: Mercier, J., & Bédard, M. (2016). An educational neuroscience perspective on tutoring: To what extent can electrophysiological measures improve the contingency of tutor scaffolding and feedback? *Themes in Science and Technology Education*, 9(2), 109-125.

URL: http://earthlab.uoi.gr/theste