

Mental Workload, Engagement and Emotions: an Exploratory Study for Intelligent Tutoring Systems

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Abstract. Modeling learners' emotional states is a promising tool for enhancing learning outcomes and tutoring abilities. In this paper, we present a new perspective of learner emotional modeling according to two fundamental dimensions, namely mental workload and engagement. We hypothesize that analyzing results from learners' workload and engagement evolution can help Intelligent Tutoring Systems diagnose learners' emotional states and understand the learning process. We demonstrate by an experiment involving 17 participants that learners' mental workload and engagement are closely related to specific emotions with regard to different learning phases.

Keywords: Mental workload, Mental engagement, Emotion modeling, ITS

1 Introduction

Endowing Intelligent Tutoring Systems (ITS) with abilities to wisely assess and monitor learners' affective and cognitive state has been an important research thrust over few past decades [1-3]. Several ITS with physio-cognitive models aiming to provide intelligent assistance, efficient adaptation and more realistic social communication were developed in the scope of reaching optimal interaction conditions, improving adaptability, enhancing learners' overall performance, skill acquisition and productivity [5-7].

In parallel, a growing body of research in the field of artificial intelligence, human computer interaction, cognition and neuroscience presented various models tracking shifts on users' alertness; engagement and workload and have been successfully used in closed-loop systems or simulation environment [2, 3, 8]. By assessing users' internal state, these systems were able to adapt to users' information processing capacity and then to respond accurately to their needs. The major part of these systems was based on two fundamental mental metrics, namely, mental workload and mental engagement.

Despite disagreement about its nature and definition, mental workload can be seen in terms of human information processing. It reflects the amount of the mental effort and energy invested as in a particular task. Mental engagement is more related to the

level of mental vigilance and alertness. It gives also a wide indication about the level of attention and motivation.

The integration of affective models in ITS added an empathic and social dimension into tutors' behaviors [6, 10]. However there is still a lack of methods helping tutors to analyze more deeply the emotional state of the learner and to diagnose and understand accurately the cognitive origin of an emotion. ITS are still mainly based on learners' performance in analyzing learning process and learners' skill acquisition [4-7]. Providing ITS with adapted tools and models to relate the affective reaction of a learner to his internal mental state can provide a new perspective for tutoring.

In this paper we present an exploratory study of emotions, mental engagement and workload within an educational environment. In particular, we performed an experiment to analyze the behavior of the computed mental metrics with regards to learners' emotional states.

2 Previous Work

Developing EEG indexes for workload assessment is an important field especially in laboratory contexts. A variety of linear and non-linear classification and regression methods were used to determine mental workload in different kinds of cognitive tasks such as memorization, language processing, visual, or auditory tasks. These methods used mainly EEG Power Spectral Density (PSD) bands combined with machine learning techniques [1, 8, 9]. In our previous work, we developed an EEG workload index based on Gaussian Process Regression (GPR) using data gathered from strict laboratory conditions [11]. The index showed to precisely reflect users' workload variation in several cognitive task.

Pope and colleagues [2] at NASA developed an EEG-engagement index based on brainwave band power and applied it in a closed-loop system to modulate task allocation. Performance in a vigilance task improved when this index was used as a criterion for switching between manual and automated piloting. Performance improvement was reported using this engagement index for task allocation mode (manual or automated). In this paper, we propose to explore the behavior of these mental metrics in a learning environment with regards to a self-reported emotion. The major contribution of this study is to present the different trends in engagement and workload with regards to emotional state within an educational context.

3 Methodology

Our experimental setup consists of a 6-channel EEG headset sensor and two video feeds. All recorded sessions were replayed and analyzed to accurately synchronize data using necessary time markers. 17 participants were recruited for this research. All participants were briefed about the experimental process and objectives and signed a consent form and were equipped with the EEG-cap. The experimental process consisted on a 10-minutes baseline followed three successive learning activities in trigonometry:

Pretest. This task involved 10 (yes/no/no-response) questions that covered some basic aspects of trigonometry (for instance: “is the tangent of an angle equal to the ratio of the length of the opposite over the length of the adjacent?”). In this part, participants have had to answer to the questions without any interruption, help or time limit.

Learning Session. In this task, participants were instructed to use a learning environment covering the theme of trigonometry and specially designed for the experiment. Two lessons were developed explaining several fundamental trigonometric properties and relationships. The environment provides basic definitions as well as their mathematical demonstrations. Schemas and examples are also given for each presented concept. Several concepts on trigonometry were recalled and the links between the different concepts was clearly explained

Problem solving. Problems presented during this task are based on participants’ ability to apply, generalize and reason about the concepts seen during the learning session. No further prerequisites were required to successfully resolve the problem except lessons’ concepts. However a good level of implication and concentration is needed to solve the problems. A total of 6 problems with a gradually increasing difficulty level were selected and presented in the same order for all participants. Each problem is a multiple-choice question illustrated by a geometrical figure. A fixed time limit is imposed for each problem varying according to its difficulty level. The problem-solving environment provided also a limited number of hints for each problem.

3.1 Subjective reporting of emotional state

After completing each task level (pretest, learning session, or after each problem), participants were asked to evaluate their emotion during the last task execution. Two axes were presented for the learner. The first axis corresponds to the emotional valence and the second axis links the emotional activation. Four main emotional states were then derived: **Q1** (positive valence, high activation), **Q2** (positive valence, low activation), **Q3** (negative valence, high activation) and **Q4** (negative valence, low activation). In order to help learner situate their emotional state examples of emotions which might arise in each state were given (e.g. interest, joy for Q1, confidence, relax for Q2, confusion, frustration for Q3 and boredom, disengagement for Q4).

3.2 EEG Recording

EEG signals were received from sites P3, C3, Pz and Fz as defined by the International 10-20 Electrode Placement System (Jasper 1958). Each site was referenced to Cz and grounded at Fpz. Two more active sites were used namely A1 and A2. Impedance was maintained below 5 Kilo Ohms and the recorded sampling rate was at 256 Hz. A 60-Hz notch filter was applied during the data acquisition to remove EEG noise. In addition, an artifact rejection heuristic was applied to the recorded data using a threshold on the signal power with regards to the baseline. For each participant, EEG data recorded from each channel were transformed into a power spectral density using

a Fast-Fourier Transform (FFT) applied to each 1-second epoch with a 50 % overlapping window multiplied by the Hamming function to reduce spectral leakage.

3.3 Computing the engagement index

As previously mentioned, a developed an engagement index was used in closed-loop system to assist pilot with regards to their mental engagement [2]. This index uses three EEG bands: **Theta** (4–8 Hz), **Alpha** (8–13 Hz) and **Beta** (13–22 Hz). The *ratio* used was: $\text{Beta} / (\text{Alpha} + \text{Theta})$. This *ratio* was also found as being the most effective when validated and compared to many other indices [8]. In our study, we used this index within a 40s window sliding technique to smooth the behavior of this index.

3.4 Computing the workload index

In order to compute the mental workload an EEG metric, we used our workload assessment model based on kernel Gaussian Process Regression and principal component analysis (PCA) algorithm. Detailed description of this model is presented in [11].

4 Results and Discussions

Our first investigation was to evaluate the progression of the workload and engagement level across the learning tasks. A repeated measures ANOVA revealed that there were significant changes in the EEG_Workload between the learning activities $F(3.23, 51.61) = 2.76, p < 0.05$. Degrees of freedom were corrected using the Greenhouse-Geisser estimates of sphericity ($\epsilon = 0.46$). Post hoc results showed that the EEG_Workload measures significantly increased during the learning session when compared with the pretest ($p < 0.05$). This increase can be explained by the effort produced by learners in understanding concepts and acquiring skills in the learning phase compared to the pretest session where learners responded to questions that did not require particular mental effort. In fact, during pretest no pressure was put on learners who had simply to situate their knowledge in trigonometry. Repeated measures ANOVA revealed no significant change in the engagement index across overall activities $F(3.66, 58.70) = 0.690, p = \text{ns}$, Greenhouse-Geisser correction $\epsilon = 0.52$). However, an expected significant decrease in learners' engagement was registered between the beginning of the lesson and the end of the problem solving phase ($p < 0.05$). In fact, switching from the pretest phase to the learning session (or from a problem to another) can have no effect on the level of engagement, vigilance or alertness of a learner. However, the engagement tended to decrease in general and this effect tended to be more pronounced at the end of the experiment. This trend is expected as the alertness of the learners can be reduced by the fatigue. The opposite trend was registered in learners' workload behavior. Mental workload significantly increased from the beginning to the end of the learning interaction. This tendency is also expected as the problem solving task is more mentally demanding than pretest or learning session (see Fig.1).

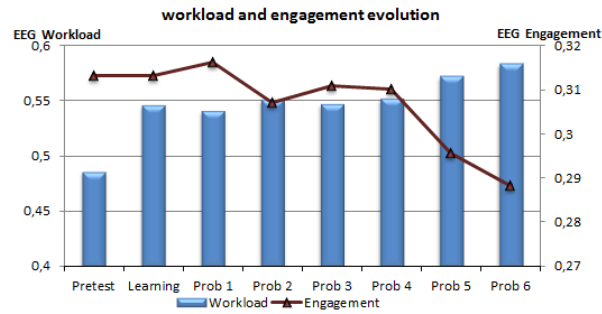


Fig. 1. Mean learners' workload and engagement for each activity.

Our next concern was to evaluate how learners reported their emotions with regards to the mental workload and engagement metrics. A one-way ANOVA showed that there is a significant effect of the emotional state reported by the learners on the engagement, $F(3, 132)=3.32, p < 0.05$ and workload $F(3, 132)=4.52, p < 0.05$ for all participants. Specifically, the analysis of this result revealed that mean engagement index values were significantly higher when learner's emotional state was in Q1 (Positive valence and high activation: $M = 0.568, SD = 0.29$) compared to the other quadrants (see figure 2). Giving this result, we can state that positive emotions arising in Q1 (such as interest) seem to lead to the highest level of user engagement. Emotional state Q1 presented also the lowest value of the workload index: $M = 0.51, SD = 0.09$. However, the highest workload value was registered in the Q3 emotional state (Negative valence and high activation: $M = 0.68, SD = 0.13$). This suggests that negative emotions with high activation (e.g. confusion) can signal a high level of mental workload.

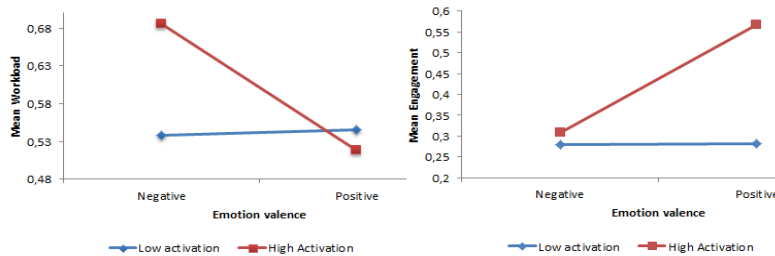


Fig. 2. Workload and engagement interaction with emotional valence and activation

A closer look to these results leads us to notice that higher level of alertness and attention elicit a high emotional activation however these emotions tended to be positive when the mental demand is low and negative in the opposite case. For example if a learner is highly involved in resolving a difficult problem and involves a high mental focus, emotions such as confusion or frustration could emerge during the activity. Lowest engagement value was recorded for Q4 (Negative valence and low activation: $M = 0.27, SD = 0.19$). One-way ANOVA also confirmed this significant impact of emotional state on workload and engagement during the learning phase and the problem solving phase when these activities are taken separately. Two factorial ANOVA were also performed to test the main effects and the interaction effect of the emotional

valence (positive, negative) and emotional activation (high, low) on workload and engagement. A significant main effect was obtained for emotional valence on workload $F(1,99)=4,390$ $p<0,05$ and for engagement $F(1,99)=6.237$ $p<0.05$. The interaction of the valence and the activation was also significant on both workload and engagement.

5 Conclusion

In this paper we presented an empirical study of workload and engagement metrics extracted from EEG signals with regards to reported emotional state. Workload and engagement indexes were analyzed with different learning activities of trigonometry. Results showed that there is significantly impact of these metrics on the reported emotion. High level of workload indicated the elicitation of negative emotions whereas engagement level was mainly associated with positive emotions. Future works involve developing a tutor which reacts in real time with the mental metrics. Moreover different strategies for handling and managing mental effort will be explored.

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