

# Assessment of Learners' Attention while Overcoming Errors and Obstacles: An Empirical Study

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**Abstract.** This study investigated learners' attention during interaction with a serious game. We used Keller's ARCS theoretical model and physiological sensors (heart rate, skin conductance, and electroencephalogram) to record learners' reactions throughout the game. This paper focused on assessing learners' attention in situations relevant to learning, namely overcoming errors and obstacles. Statistical analysis has been used for the investigation of relationships between theoretical and empirical variables. Results from non-parametric tests and linear regression supported the hypothesis that physiological patterns and their evolution are suitable tools to directly and reliably assess learners' attention. Intelligent learning systems can greatly benefit from using these results to enhance and adapt their interventions.

**Keywords:** Learners' attention, assessment, serious game, physiological sensors, EEG, regression model

## 1 Introduction

The increased use of Computer-Based Education over the last decades encourages the investigation of new and engaging learning environments. Currently, serious games are used to train or educate learners while giving them an enjoyable experience. They have been considered as the next wave of technology-mediated learning. Several studies have assessed their potential as learning tools [1-3]. They have concluded that the integration of games into learning systems have enhanced the desired learning outcomes. Amory and colleagues have identified game elements that learners found interesting or useful within different game types such as in-game rules, immersive graphical environment and interactivity just to name a few [4]. Beside these distinctive design elements that seem necessary to stimulate learners' motivation, other researchers however have reported that consequences of different game elements, such as risks, errors, and obstacles, seem to be more relevantly correlated with learners' motivation and attention [5]. Indeed, computer games typically put traps and obstacles in the way of the player thus requiring more attention while overcoming them in order to properly progress through the rest of the game. In contrast to the significant amount of research effort in the area of serious games, less has been done however regarding the assessment of learners' attention while overcoming errors and obstacles. These situations are therefore the specific area of interaction that our research focuses on to assess learners' attention.

Traditional assessment usually involves measuring performance, time spent, and response time as main indicators of learners' attention. However, researchers have recently used psychological motivational models, physical sensors, and a combination of both to assess complex learners' states such as motivation, attention and engagement during serious game play [2, 6, 7]. Nevertheless, further studies are required to possibly identify learners' physiological evolution while overcoming errors and obstacles. Consequently, a learning system can customize its learning process by adapting learning strategies in order to respond intelligently to learners' needs, objectives and interests. The present paper aims at highlighting some of the relevant physiological patterns that occur in learners and correlating them with learners' attention while overcoming errors and obstacles in a serious game. We have therefore carried out an empirical study to assess learners' attention using Keller's ARCS psychological model combined with physiological recordings, namely heart rate (HR), skin conductance (SC) and brainwaves (EEG). We ask in this paper the two following research questions: can we identify relevant physiological manifestations in learners' attention while overcoming errors and obstacles? If so, can we reliably predict learners' attention by establishing a reliable AI model?

The organization of this paper is as follows: in the next section, we present previous work related to our research. In the third section, we explain our empirical approach in assessing learners' attention. In the fourth section, we detail our experimental methodology. In the fifth section, we present the obtained results and discuss them, in the last section, as well as present future work.

## 2 Related Work

Assessing learners' states is of particular importance in establishing proper strategies and understanding the processes that might explain differences between learners' knowledge acquisition. Unlike human tutors, intelligent systems cannot exclusively rely on observational cues, such as posture and gesture, to infer emotional and cognitive states, such as motivation and engagement. Several studies have been therefore proposed to intelligently identify these states through the use of physical sensors. One of those studies used biometric sensors (HR, SC, electromyography and respiration) and facial expression analysis to develop a probabilistic model of detecting students' affective states within an educational game [8]. Another study used four different sensors (camera, mouse, chair, and wrist) in a multimedia adaptive tutoring system to recognize students' affective states and embedded emotional support [9].

In the particular case of learners' attention, performance and response time have been generally used as assessment metrics. Recent studies have reported significant results in assessing learners' attention using others cues. Qu and colleagues for example used a Bayesian model to combine evidence from the learner's eye gaze and interface actions to infer the learner's focus of attention [10]. Kuo-An and Chia-Hao applied fuzzy logic analysis of students facial images when participating in class to prevent erroneous judgments and help tutors deal with students attentiveness [11]. Another multimodal approach by Peters and colleagues investigated a user attention model by establishing three core components (gaze detection, neurophysiological detection, and a user attention representation module) for human-agent interaction [12]. The authors proposed to establish patterns of behavior and attention allocation useful for endowing autonomous agents with more natural interaction capabilities.

Finally, in video games context, commercial helmet-embedded sensors combining multiple channels such as EEG and facial EMG, have been designed to recognize game relevant player states, such as engagement, attention, and boredom [13].

It is clear that combining physical sensors and theoretical model is best for addressing learners' attention during a specific activity or context. However, this combination has been rarely done. For example, [14] used a self-report questionnaire (Keller's ARCS model) and a portable EEG to examine attention and motivation in a virtual world. We also aim in this work to examine the attention state but in a completely different goal and perspective. Indeed, in contrast to Rebolledo-Mendez and colleagues' work, we have chosen to assess learners' attention while overcoming errors and obstacles during serious game play. We have also chosen to combine the ARCS model and different physiological sensors (HR, SC, and EEG) as our assessment metrics. We chose serious games for they constitute a powerful learning environment to support attention and motivation [2]. They can accelerate learning and support the development of various skills, such as cognitive thinking and problem solving skills [15]. In fact, many studies have been increasingly trying to define specific features of games that enhance learning [1, 2, 16]. They have stated that these environments increase attention state through the use of traps and obstacles to allow learners for instance to take risks and overcome obstacles. We are interested in assessing this specific state in learners and the next section will present the method used to assess learners' attention.

### 3 Assessment of Learners' Attention

The key issue in this paper is related to the assessment of learners' attention in serious games environment. The *Attention* category of the ARCS model of motivation [17] has been chosen to theoretically assess learners' attention. Indeed, Keller's model is of particular interest in our study since it separately considers the attention dimension and it has been used in learning, training and games [18]. Even the use of a theoretical model may offer some insight into the learners' attention directly from the learners but it remains insufficient. Several objective measures, however, are not dependent on a learners' perception and generally include independent measures such as performance, time spent in a game, response time, and physiological reactions. In our empirical assessment approach, we decided to assess learners' attention by using non-invasive physiological sensors (SC and HR). These sensors are typically used to study human affective states [19]. Furthermore, we decided to add another interesting and important sensor: EEG. Indeed, brainwave patterns have long been known to give valuable insight into the human cognitive process and mental state[20].

This paper also explores the intricate relationship between the *Attention* category in the ARCS model and its corresponding EEG fingerprint expressed in the form of a ratio known as the attention ratio (Theta/Low-Beta) [21]. Indeed, according to the authors, a negative correlation exists between the attention ratio and learners' attention. A high attention ratio is usually correlated with excessive Theta and consequently inattentive state. Conversely, a low attention ratio is normally correlated with excessive Low-Beta brainwave activity reflecting attentive state in adults. In addition, it is common knowledge throughout the neuro-scientific community that investigations of cerebral activity limited to one area of the brain may offer misleading information regarding complex states such as attention. We have therefore investigated different

cerebral areas to study simultaneous brainwave changes. The idea is to analyze, in a joint venture, both physiological and cerebral signals to determine, or at least estimate, their correlations with learners' attention while overcoming errors and obstacles during serious game play. To that end, prediction models will be constructed using theoretical and empirical data. A detailed description of all these possibilities is given in the experiment and results sections.

## 4 Experiment

The participants were invited to play the serious game called FoodForce from the World Food Program of the United Nations intended to educate players about the problem of world hunger. FoodForce is comprised of multiple arcade-type missions, each intended at raising players' awareness towards specific problems regarding world-wide food routing and aid. FoodForce also presents players' objectives in a short instructional video before the beginning of each mission. A virtual tutor also accompanies the player throughout each mission by offering various tips and lessons relative to the obstacles and goals at hand. Following the signature of a written informed consent form, each participant was placed in front of the computer monitor to play the game. A baseline was also computed before the beginning of the game. A pre-test and post-test were also administered to compare learners' performance regarding the knowledge presented in the serious game.

The missions we are interested in investigating in this paper are missions 3 and 5. Mission 3 instructs players to drop 10 food packets from an airplane to an alley on the ground. Before dropping a packet, a player has 5 seconds to calculate the speed and strength of the wind before releasing the food ideally as close to the center of the lane as possible. *Errors* in this mission are reflected through the obtained final score. Furthermore, the tutor intervened and gives an immediate feedback after each drop. Mission 5 is concerned with driving food trucks in dangerous territories and get through *obstacles* such as quickly replacing flat tires and managing diplomatically through intimidation attempts by angry locals. Players loose one truck of food for each failed attempt to successfully overcome an obstacle in this mission.

The motivational measurement instrument called Instructional Materials Motivation Survey IMMS [17] was used following each mission to assess learners' motivational state. SC and HR sensors were attached to the fingers of participants' non-dominant hands, leaving the other free for the experimental task. An EEG cap was also conveniently fitted on learners' heads and each sensor spot slightly filled with a proprietary saline solution. EEG was recorded by using a cap with a linked-mastoid reference. The sensors were placed on three selected areas (F3, C3 and Pz) according to the international 10-20 system. The EEG was sampled at a rate of 256 Hz. A Power Spectral Density (PSD) was computed to divide the EEG raw signal into the two following frequencies: Theta (4-8 Hz) and Low-Beta (12-20 Hz) in order to compute the attention ratio (Theta/Low-Beta) as described above. To reduce artifacts, participants were asked to minimize eye blinks and muscle movements during recording. A normalization technique (min-max) was applied to all physiological data.

We computed an index representing players' physiological evolution throughout the mission with regards to each signal signification. This index, called Percent of Time (PoT), represents the amount of time, in percent, that learners' signal amplitude is lower (or higher) than a specific threshold. The threshold considered for each signal

is the group's signal average for each mission. The PoT index is a key metric enabling us to sum-up learners' entire signal evolution for a mission. For SC and HR, the PoT index will be computed for values *above* the threshold since we are looking for positive evolutions when playing a serious game. Conversely, for EEG attention ratios, a PoT index was calculated when learner's attention was *below* the threshold as explained previously in section 3. Fig. 1 illustrates a learner's EEG attention ratio evolution during 20 seconds one mission. The computed PoT for the selected 5 second window in this figure would be 40% (2 values below divided by 5 values) and 80% for the entire 20 seconds (16 values below divided by 20 values overall).

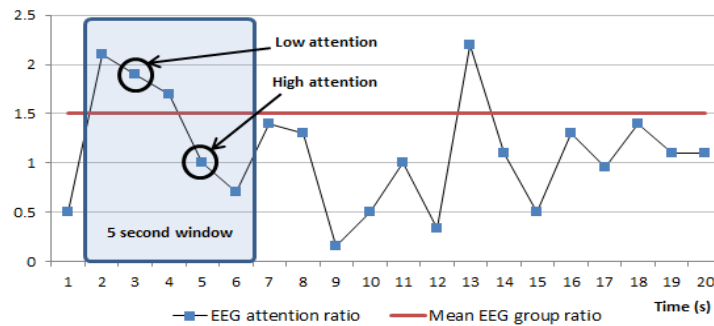


Figure 1. Learner's attention ratio evolution

Thirty three volunteers (11 female) took part in the study in return of a fixed compensation. Participant's mean age was  $26.7 \pm 4.1$  years. Four participants (2 female) were excluded from the EEG analysis because of technical problems at the time of recording. The next section will detail the experimental results and findings.

## 5 Results

Our statistical study relied on non-parametric statistical tools because our sample population is small (29 participants) and no justifiable assumptions could be made with regards to the normal distribution of the data. Hence, Wilcoxon signed ranks test and Spearman's rho ranks test have been used. Furthermore, reported significant p-values were all computed at the .05 significance level (95% confidence).

First, we report significant positive change regarding learners' knowledge acquisition. Indeed, we administered pre-tests and post-tests questionnaires pertaining to the knowledge taught in the serious game and compared results using the Wilcoxon signed ranks test ( $Z = 4.65$ ,  $p < 0.001$ ).

Second, we report results of correlation run on data of missions 3 and 5. Analysis of mission 3 showed that a significant relationship between reported attention and three physiological sensors (*PoT-F3 index: spearman's rho=.34*,  $n=29$ ,  $p<.001$ ; *PoT-SC index: spearman's rho=.536*,  $n=29$ ,  $p<.01$ ; *PoT-C3 index: spearman's rho=.532*,  $n=29$ ,  $p<.01$ ). Similar results have been found for reported attention regarding mission 5, *except for the PoT-F3 index (PoT-C3 index: spearman's rho=.62*,  $n=29$ ,  $p<.01$ ; *PoT-SC index: spearman's rho=.503*,  $n=29$ ,  $p<.01$ ). These results positively answer our first research question (can we identify relevant physiological manifestations in

learners' attention while overcoming errors and obstacles?). Indeed, learners' attention while overcoming errors and obstacles can reliably be monitored and related to changes in skin conductance and F3 and C3 EEG sensors.

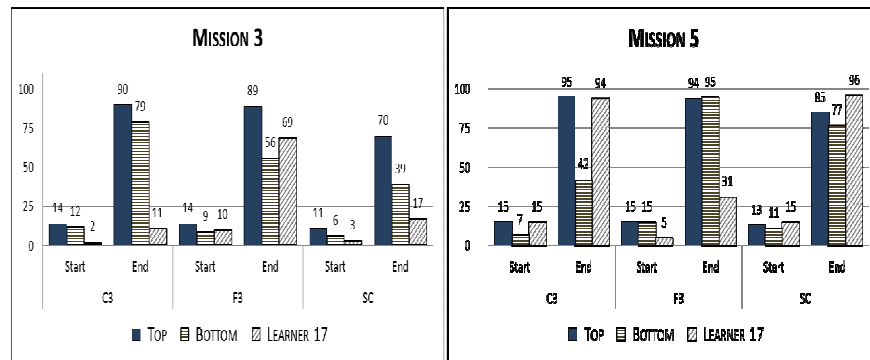
Third, in order to answer our second research question (can we reliably predict learners' attention by establishing a reliable AI model?), we ran linear regressions to predict learners' reported attention during each mission. Our prediction models used all computed PoT indexes and learners' mission final score as predictor variables (PoT-SC, PoT-HR, PoT-F3, PoT-C, PoT-Pz and Score) and the stepwise method for variable selection. Table 1 reports the results of multiple linear regressions.

Regression model	F	Sig.	Adjusted R <sup>2</sup>	Significant predictors
<i>Mission 3</i>	F <sub>2,26</sub> =18.304	.000 (*)	.553	PoT-F3: Beta=.560 p=.000 PoT-SC: Beta=.437 p=.002
<i>Mission 5</i>	F <sub>1,27</sub> =28.409	.000 (*)	.495	PoT-C3: Beta=.716 p=.000

(\*) Significance at the 0.05 level

**Table 1.** Results of regression models

In our prediction models, EEG attention ratios are significant predictors for attention for the duration of both missions. These results seem to show the relevance and importance of adding the EEG in assessing learners' attention evolution, even more so when attention cannot be clearly established by the use of HR and SC alone. Furthermore, our AI model is sensitive to the type of mission as well as the time window for assessment. Indeed, as described earlier in section 4, mission 3 and mission 5 involve different skills from a learner that are represented by changes in F3 and C3 respectively [22]. During mission 3, while trying to avoid errors and mistakes as much as possible, learners will tend to rely mostly on the frontal cortex (F3) because it is known to be strongly implicated in taking quick decisions under pressure. Conversely, during mission 5, while trying to overcome obstacles, a more "generalized" problem-solving approach is used and thus the central region of the brain (C3) seems to be the most solicited. An example of this situation is illustrated in fig. 2.



**Figure 2.** PoT index evolution for missions 3 and 5

This figure presents PoT index evolutions of 3 learners (TOP, BOTTOM and LEARNER 17) in 2 distinct moments: the beginning (*Start*) and the end (*End*) of the mission. The blue filled bar (Top) represents a learner whose reported attention is highest for both missions. Conversely, the brown horizontal sprites (Bottom) represent a learner whose reported attention is lowest. Learner 17 (the gray diagonal sprites) has reported a very low attention in mission 3 but a very high attention in mission 5. We can see by the results that the predictors found in the model for mission 3 (PoT-F3 and PoT-SC) can distinguish between learners with high versus low attention. Learner 17 has the same trends (PoT-F3 and PoT-SC) as the bottom learner. Conversely, the predictor found in the model for mission 5 (PoT-C3) is the one to look at in order to separate learners' attention. Again we can clearly see that learner 17's PoT-C3 trend is almost the same as the top learner.

## 6 Conclusion and Future Work

In this paper, we have assessed learners' attention while overcoming errors and obstacles in a serious game using the ARCS theoretical model as well as three objective physiological measures: HR, SC and EEG. Results have shown that learners' attention was correlated with specific physiological manifestations, especially observable in the evolution of the EEG PoT indexes (C3 and F3). We have also built significant regression models that have shown to be valuable tools in predicting learners' attention using physiological patterns' evolution for each mission.

The obtained results are very encouraging to their future integration in an adaptive real-time attention detection prototype for an intelligent learning system. This integration will positively contribute to learning because reliable real-time objective assessment of learners' attention is now possible, since we can rely on this assessment as a substitute for self-reports that can disrupt a learning session. Furthermore, it is possible to enrich an intelligent system to properly adapt its interventions during a specific activity or context based on task type. However, one possible limitation of this study is the dependence of all categories of the ARCS model. In further work, we plan to address a complementary study in order to highlight other distinctive, or even common, physiological patterns related to other ARCS categories (relevance, confidence, and satisfaction) and the overall motivational state of the learner.

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