Measuring the Engagement of the Learner in a Controlled Environment using Three Different Biosensors

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Keywords: Computer Applications, Education, Elearning, Affective Computing.

Abstract: Irrespective of the educational model, the major challenge is how to achieve maximum efficiency of the education process and keep learners engaged during learning. This paper investigates the relationship between emotions and engagement in the E-learning environment, and how recognizing the learners emotions and changing the content delivery accordingly can affect the efficiency of the E-learning process. The proposed experiment aims to identify ways to increase the engagement of the learners, hence, enhance the efficiency of the learning process and the quality of learning. A controlled experiment was conducted to investigate participants emotions using bio sensors such as eye tracker, EEG, and camera to capture facial images in different emotional states. One-way analysis of variance (ANOVA) test and t-Test was carried out to compare the performance of the three groups and show if there was an effect of using the affective E-learning system to improve the learners performance. Our findings support the conclusion that using bio sensors as a quantitative research tool to investigate human behaviours and measure emotions in real time can significantly enhance the efficiency of E-learning.

1 INTRODUCTION

The efficiency of education is highly dependent on the delivery method. Students learn best when they actively participate in the learning process, when they are engaged and motivated to learn, and when they can build on their existing knowledge and understanding (L.Brown et al., 2000).

For all kinds of education: traditional, progressive, e-learning or blended learning, the major challenge is how to achieve maximum efficiency of the education process and keep learners engaged during the learning process. According to Bangert-Drowns Pyke, truly engaged learners are behaviorally, intellectually, and emotionally involved in their learning tasks (Bangert-Drowns and Pyke, 2001). In face - to - face teaching, experienced teachers recognize the engagement level of the students and react accordingly. They change their teaching method during the class to grab the students attention. Mixing different teaching methods and strategies in the teaching process engages students and efficiently achieves the set educational goals. This strategy can be adoptable in the traditional and progressive education forms, where the teacher has direct contact with students and can recognize their engagement level. On the other hand, the absence of face-to-face communication in e-learning environment, lowers the interactivity level and, accordingly, the students engagement, and increases the need for other alternatives. Recognizing the students engagement is not straightforward in the e-learning model, where there is no direct contact between the instructor and learner. Researchers found that emotions and affect influence a wide diversity of cognitive processes that affect learning, such as perception, attention, social judgment, cognitive problem-solving, decision-making, and memory processes (Huntsinger and Clore, 2007; Lerner and Loewenstein, 2003; Spackman and Parrott, 2000).

From an educational point of view, emotions can be classified into positive and negative emotions. Positive emotions encourage students to engage and achieve, such as joy (enjoyment of learning), hope and pride. In this case, Csikszentmihalyis model of flow can be applied; in which there is a zone where people can concentrate their attention so intensely on solving a problem or doing things that they lose track of time (Csikszentmihalyi, 2008) Such flow is optimal experience that leads to happiness and creativity. If the task is not challenging enough or too challeng-

El-Abbasy, K., Angelopoulou, A. and Towell, T.
Measuring the Engagement of the Learner in a Controlled Environment using Three Different Biosensors.
DOI: 10.5220/0006788202780284
In *Proceedings of the 10th International Conference on Computer Supported Education (CSEDU 2018)*, pages 278-284
ISBN: 978-989-758-291-2

ing, negative emotions such as anger, anxiety, shame or boredom affect the efficiency of learning. These emotions can highly affect the learning and achievement of the students. Hence, it is essential for teachers to understand and deal with the students emotions. (Pekrun, 2012)

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Emotions can affect students engagement, which in turn influences their academic learning and achievement. Engagement can be regarded as a mediator between students emotions and their achievements. According to Pekrun and Linnenbrink Garcia, engagement can be categorized into five types: Cognitive, motivational, behavioural, cognitive-behavioural, and social-behavioural (Linnenbrink-Garcia, 2011)

Studies found that negative emotions such as anxiety, shame, boredom, anger, and hopelessness were connected to task-irrelevant thinking and reduced flow, while enjoyment related negatively to irrelevant thinking and positively to flow (Pekrun, 2010)

In this research, an affective e-learning platform has been designed to read and recognize the learners emotions in real time during the e-learning process using a computer and bio-sensors, and use these reading to simulate the traditional learning environment and change the learning materials when negative emotions detected. A pilot study has been conducted on participant students to evaluate the effect of the system on the performance and achievement of the students. The pilot study is a lab experiment, where the researcher is able to control all factors and conditions that could have an effect (like determining the precise timing and configuration of all stimuli and excluding any problematic side effects). This study aims to examine the research instruments on a small scale. 15 participants have participated in this pilot study, representing 20 percent of the sample size of the main study (75 subjects), which according to Baker (Baker, 2014) is a reasonable number to conduct a pilot study.

Our finding suggests that using the affective e-learning platform helped to enhance the performance of the participant students compared to those who used a regular e-learning platform.

2 METHODOLOGY

The nature of work for this research is rooted in empirical software engineering using a controlled experiment method to test the hypotheses, create and use an intervention which is the affective computing system. This system, which will recognize the participants emotions and control the e-learning materials delivery, is the independent variable that will be manipulated to measure its effect on the dependent variable, which will be the participants performance during an assessment.

2.1 Research Hypotheses

1. If the students emotions can be recognized by computers during the E-learning process, then the level of engagement can be detected. Is emotion recognition during e-learning associated with level of engagement?
2. If the students level of engagement can be detected during the E-learning process, then the learning process can be enhanced because different teaching strategies can be applied by the E-learning system to maintain or increase the level of engagement. Can level of engagement during e-learning be enhanced by modifying the delivery of materials according to affective state?
3. Optimizing level of engagement during e-learning will maximize task performance.

2.2 Participants

15 participants were recruited to this pilot study. These participants were volunteered from the students of the computing department in a University. They were within the 18-25 age group and had self-reported normal ranges of hearing and vision. They were assigned at random to three groups:

Table 1: Participant demographic by group.

Variable	Group 1	Group 2	Group 3
Age, years, mean	19.4	22.8	21.4
+/- SE	+/- 0.51	+/- 0.58	+/- 0.67
Gender			
Male	5	4	4
Female	0	1	1
Learning disability			
Yes	0	0	0
No	5	5	1

- **Group 1: [The Control Group]:** This group consisted of 5 participants and used the traditional (face - to - face) education approach.
- **Group 2:** This group consisted of 5 participants and used e-learning education approach.
- **Group 3:** This group consisted of 5 participants and used affective e-learning approach (figure 1).

Figure 1: A student using the affective e-learning system.

2.3 Procedure

Group 1 was the control condition where no e learning intervention was used. Group 2 applied e-learning then compared it to group 1, and finally, group 3 applied the affective e-learning intervention and compared it to group 2. All participants had to complete a pre-study questionnaire at the beginning of the experiment to collect information about the user and detect any learning difficulties that may affect the results of the experiment. In addition, the participants had to read a participation information sheet), fill and sign consent form, and finally a photograph and video release form. Then, different procedures were used with the three groups according to the following plan:

Group 1 [The Control Group]. The participants were asked to attend a traditional (face - to - face) class for a selected topic conducted by the course instructor (for about 40 minutes), then preform a written assessment related to the selected topic (for about 20 minutes), and finally, answer a short oral post-study questionnaire (for about 5 minutes).

Group 2. The participants were asked to engage with e-Learning materials (using a computer) for the same topic as above, developed by the researcher, without the presence of the instructor (for about 40 minutes), then preform a written assessment similar to the one used with group 1 (for about 20 minutes), and finally, answer a short oral post-study questionnaire (for about 5 minutes).

Group 3. The participants were asked to engage with affective e-learning system (using a computer, biosensors, and learning materials) for the same topic as above, developed by the researcher, without the presence of the instructor (for about 40 minutes), then preform a written assessment similar to the one used with group 1 (for about 20 minutes), and finally, answer a short oral post-study questionnaire (for about 5 minutes).

2.4 Equipment

The following equipment was used by the three groups:

- **Group 1:** A white board in a traditional classroom setting was used to present the materials by the courses instructor.
- **Group 2:** Laptop: The main platform (Intel Core I5, 8GB RAM), which was used to present the e-learning materials.
- **Group 3:** This group have used the affective e-learning system equipment, which consists of:

1. Laptop: The main platform (Intel Core I5, 8GB RAM), which was used to run the system software and hardware to create the experiment process, interacting with the user, collecting and analyzing the data.
2. Eye tracker: Screen based eye tracking device to record eye movements at a distance. The eye tracker was mounted below the screen and the student was seated in front of it. The eye tracker is using screen based stimulus materials to quantify visual attention.
3. EEG headset: A 14 channel wireless EEG headset used to record electrical activity generated by the brain by placing electrodes on the scalp in order to measure attention and emotional arousal.
4. Web Camera: A web camera attached to the laptop to capture the students facial expressions and use a software to recognize his / her emotions in order to detect attention and emotional arousal.

2.5 Software

The following software was used by the three groups:

- **Group 1:** No software was needed for this group.
- **Group 2:** Windows 7 professional, and windows media player.
- **Group 3:** iMotions: A biometric research platform used for multimodal human behavior researches (figure 2). This platform provides the ability to perform real-time, frame-by-frame analysis of the emotional responses of users, detecting and tracking expressions of primary. Three modules are used in this research:

1. Eye Tracking Module: Eye tracking was used to measure the visual attention, engagement, and emotional arousal. The following metrics were used by this module: gaze points, fixation, and pupil size / dilation.

2. EEG Module: EEG was used to measure attention and emotional arousal. The following metrics were used by this module: Engagement / boredom, frustration, Excitement long term, and Excitement short term.

3. Facial Expressions Module: Facial expressions was used to read and detect the users positive and negative emotions in order to detect attention and emotional arousal. The following metrics were used by this module: joy, anger, sadness, neutral, positive, and negative.

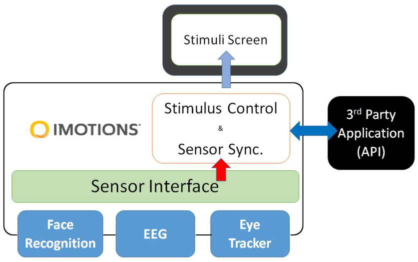

Figure 2: The affective e-learning system diagram for pilot study.

2.6 Control API

An API module is designed to receive the biometric sensors data, analyze it, and use it to control the e-learning materials delivery, as shown in figure 3:

- The process starts by connecting and calibrating the biosensors, then the e-learning materials is presented to the student on the laptop screen while the bio sensors is collecting the data.
- The API collects and read the data, and if a change in the sensors data was detected which may indicate a change in the emotions or attention state, the API will send a signal to the software to change the presentation material with the correspondence alternative material.
- The API continuously reads/monitors the data and provides control signals accordingly until the e-learning session is completed.

Figure 4 shows the UML interaction overview diagram, where the procedure starts, after adjusting and testing the EEG and facial expression detection sensors, by testing the eye tracking sensor, and move forward if passed to present the first e-learning material (assumed to be P1 video). Meanwhile, the API keeps reading and analysing the data provided by the sensors. If positive emotions have detected, the system will keep playing the P1 material to the end, then proceed to the next material P2. If at any time a negative emotions have detected, the API will send a signal to stop playing P1 and change to the alternative material P1a. The process will continue in the same pattern through the rest of materials (up to P5 in this example), and any alternative material will be played if needed, till the end of the materials.

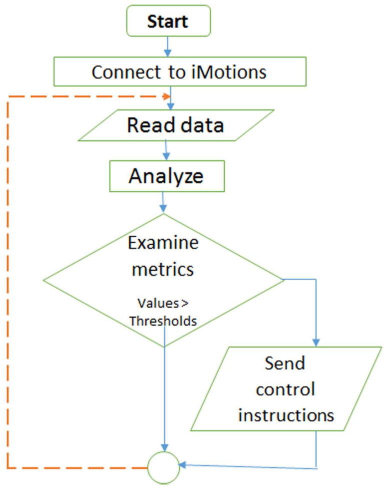

Figure 3: The API flow chart.

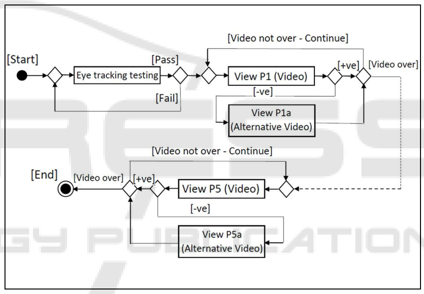

Figure 4: UML interaction overview diagram for Affective e-learning system.

3 DATA ANALYSIS

At the end of the experiment, the participants have conducted an assessment (one time for each participant) and the resulted data have been collected as an ordinal variables (test scores from 1 to 10) to be analyzed.

3.1 One-way ANOVA

As it was needed to determine whether there are any statistically significant differences between the means of three groups (with ordinal categorical normally distributed data), the one-way analysis of variance (ANOVA) test was carried out to compare the means of the three groups and show if there is an effect of using the affective e-learning system of the learners performance.

Table 2: One way ANOVA test results, 3 groups.

Source	df	SS	MS	F*	p-value
Factor	2	84.5	42.25	4.18	0.04
Error	10	9.5	0.95		
Total	12	94			

Table 3: Two tailed t-Test results, group 1 and 2.

Source	$\bar{x}$	S^2	t	p
Group 1	6.8	2.2	0.56	2.78
Group 2	6.4	0.3		

To analyze the data, two hypothesis were made with a level of significance α =0.05. Equation (1) shows the null hypothesis H_0 , which means there is no significant difference in the performance of the three groups, while equation (2) shows the alternative hypothesis H_1, which means there is a significant difference in the performance of the three groups.

$$H_0 : \bar{x}_1 = \bar{x}_2 = \bar{x}_3 \tag{1}$$

where $\bar{x}$ = mean

$$H_1 : \bar{x}_1 \neq \bar{x}_2 \neq \bar{x}_3 \tag{2}$$

The ANOVA test results (table 2) shows that the critical F=3.89, while F*=4.18 which is larger than the critical value, and accordingly, we reject the null hypothesis and accept the alternative hypothesis which means that there is a significant difference between the performances in the three groups.

3.2 Two Tailed t-Test

Two tailed t-test statistical test with a level of significance α=0.1 (for two tailed test α =α/2=0.05) was used three times to compare the data on the different groups as following:

3.2.1 Compare Group 1 and 2

Group 1 ($\bar{x}_1$ = 6.8, S_1^2= 2.2), and group 2 ($\bar{x}_2$ = 6.4, S_2^2= 0.3), where $\bar{x}$ is the mean and S^2 is the variance, was compared according to two hypothesis. Equation (3) shows the null hypothesis H_0, which means there is no significant difference in the performance of the two groups, while equation (4) shows the alternative hypothesis H_1, which means there is a significant difference in the performance of the two groups.

$$H_0 : \bar{x}_1 = \bar{x}_2 \tag{3}$$

$$H_1 : \bar{x}_1 \neq \bar{x}_2 \tag{4}$$

Table 4: Two tailed t-Test results, group 1 and 3.

Source	$\bar{x}$	S^2	t	p
Group 1	6.8	2.2	1.8	2.78
Group 3	8.2	0.7		

Table 5: Two tailed t-Test results, group 2 and 3.

Source	$\bar{x}$	S^2	t	p
Group 2	6.4	0.3	4.02	2.78
Group 3	8.2	0.7		

The t-test results (table 3) shows that t=0.56, while p=2.78 which is larger than t, and accordingly, we accept the null hypothesis which means that there is no significant difference between the performances in the two groups.

3.2.2 Compare Group 1 and 3

Group 1 ($\bar{x}_1$ = 6.8, S_1^2= 2.2), and group 3 ($\bar{x}_3$ = 8.2, S_3^2= 0.5), where $\bar{x}$ is the mean and S^2 is the variance, was compared according to two hypothesis. Equation (5) shows the null hypothesis H_0, which means there is no significant difference in the performance of the two groups, while equation (6) shows the alternative hypothesis H_1, which means there is a significant difference in the performance of the two groups.

$$H_0 : \bar{x}_1 = \bar{x}_3 \tag{5}$$

$$H_1 : \bar{x}_1 \neq \bar{x}_3 \tag{6}$$

The t-test results (table 4) shows that t=1.8, while p=2.78 which is larger than t, and accordingly, we accept the null hypothesis which means that there is no significant difference between the performances in the two groups.

3.2.3 Compare Group 2 and 3

Group 1 ($\bar{x}_2$ = 6.4, S_2^2= 0.3), and group 3 ($\bar{x}_3$ = 8.2, S_3^2= 0.5), where $\bar{x}$ is the mean and S^2 is the variance, was compared according to two hypothesis. Equation (7) shows the null hypothesis H_0, which means there is no significant difference in the performance of the two groups, while equation (8) shows the alternative hypothesis H_1, which means there is a significant difference in the performance of the two groups.

$$H_0 : \bar{x}_2 = \bar{x}_3 \tag{7}$$

$$H_1 : \bar{x}_2 \neq \bar{x}_3 \tag{8}$$

The t-test results (table 5) shows that t=4.02, while p=2.78 which is less than t, and accordingly, we accept the alternative hypothesis which means that there is a significant difference between the performances in the two groups

3.3 Finding Correlation between the Metrics

Group 3 has examined the affective e-learning system by watching the e-learning materials while using the three biometric sensors (EEG, eye-tracker, and camera) to recognize their emotions and control the e-learning materials delivery during the experiment. The API collected in total, the average of 445,812(reading) x 5 (subjects) = 2,229,060 rows of raw data during the experiment. However, 122,598 (5.5 percent of the 2,229,060 samples) rows of the raw data were excluded because of they were invalid (misreading of the data by one or more sensors because of the users action like eye blinking, head movement, face turned away from camera, etc.). A combination of different metrics used by the three sensors was used by the API to control the delivery of the e-learning materials and decide whether to change the materials or not according to a predefined threshold for each metric. Finally, an eye tracker were used during the experiment to detect whether the user is looking into the display or not, hence, detect the level of engagement. Scatter plots and correlation coefficient r have been used to find a relationship and measure its strength and direction between the different metrics used to detect the emotions and level of engagement of the affective e-learning system user.

Table 6 summarizes the results of the correlation coefficient r between the facial expressions metrics and the EEG metric (Where green, blue, and red colors represent strong, moderate, and weak correlation in order). The table shows the results of the correlation tests between two groups of metrics representing two biometric sensors. The EEG metric (long term excitement) has a strong relationship with two facial expressions metrics (positive & joy), moderate negative relationship with other two metrics (anger & sadness), and weak or no relationship with the last two (negative and fear). The second EEG metric (short term excitement) shows a weak or no relationship with any of the facial expressions metrics. The third EEG metric (frustration) has a moderate negative relationship with three facial expressions metrics (positive, joy, and fear), and the last EEG metric has a moderate positive relationship with (positive and joy).

This can be a good indicator that the EEG metrics can be replaced by a combination of the five related metrics (positive, joy, anger, fear, and sadness). The sixth facial expression metric was not correlated with any EEG metrics and had no significant change in value when the participants emotion change detected during the experiment, hence, it can be discarded from the metrics list. Also, it was found that the two metrics (positive and joy) have the exact values during the experiment, which means we can discard one of them and use the other. Finally, the fear metric is not appropriate to be used in the learning and education context. It may be more suitable for playing horror games for example, therefore it can be discarded. On the other hand, the EEG metric (short term excitement) can be discarded as it had no correlation with any of the facial expression metrics and no significant change in the participants emotion detection.

In conclusion, the correlation tests show that the EEG metrics (Long term excitement, frustration, and engagement) can be replaced by a combination of three facial expressions metrics (positive, anger, and sadness).

3.4 Pilot Study Interpretation

- The ANOVA data analysis shows that there is a significant change in the students performance using three different approaches.
- Using t-Test analysis, shows that there is no difference when using traditional education and e-learning. Comparing the traditional education with the affective e-learning didnt show much difference as well. However, comparing the e-learning with the affective e-learning approaches, shows a significance change in the performance. This indicates that using affective e-learning may enhance the efficiency of e-learning which is the answer for the second research question.
- In the pilot study, the API used two facial expressions metrics to detect the participants emotions and change the delivery of the affective e-learning system materials. These metrics were (joy) and (sadness) (with a threshold of 0.5 for each). After the experiment, analyzing the collected data shows the learning materials have been changed three times. It is found that each time the materials have changed, there was a significant change in the value of the EEG metric (Long term excitement), which has dropped by about 33 percent of its average value. Also, the EEG metric (Frustration), which has increased by about 17 percent of its average value. Finally, the EEG metric (Engagement), which has increased by about 13 percent of its average value. This can add a value to the validity of the facial expressions sensor metrics.

Table 6: Metrics correlation.

Sensors		EEG			
	Metrics	Excitement (Long term)	Excitement (Short term)	Frustration	Engagement
Facial Exp.	Positive	0.62	0.17	-0.46	0.44
	Negative	0	0.15	-0.1	-0.09
	Joy	0.62	0.17	-0.46	0.44
	Anger	-0.46	-0.08	0.03	0.19
	Sadness	-0.47	-0.28	0.38	0.38
	Fear	-0.07	-0.02	-0.48	0.09

- Furthermore, a correlation tests show that the EEG metrics (long term excitement, frustration, and engagement) can be replaced by a combination of three facial expressions metrics (positive, anger, and sadness), hence, the EEG biometric sensor can be discarded in further study.

4 CONCLUSION AND FUTURE WORK

In this research, a small scale pilot study has been conducted in preparation for a main study. This study helped to detect some problems which can be avoided in the main study to give better results:

- Testing was carried out at different times and in different phases. In the last phase (testing the affective e-learning system), it was hard to find volunteers among students as it was the end of the academic year period and most of the students had started their vacation. Accordingly, the selection options were very limited.
- To record EEG, there is a need to have a good signal to noise ratio. In other words, all electrodes should be well connected and attached to the participants scalp to ensure a low resistance. Any poor connection for any of these electrodes may affect the quality of the data and require restarting the process. It was very difficult to maintain low resistance electrode connections within the time constraints.

The pilot study was very useful in terms of testing the equipment and the software. However, more work needs to be done to enhance the results. Few enhancements needs to be done to the API, and better materials needs to be developed. In future, having a bigger sample of participants will definitely enhance the results and give a bigger image. Moreover, the pilot study helped to decide which metrics will be used in the main study.

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